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Mestrado em Estatística e Gestão de Informação  
Master Program in Statistics and Information Management

## **MACHINE LEARNING APPROACH FOR CREDIT SCORE ANALYSIS: A CASE STUDY OF PREDICTING MORTGAGE LOAN DEFAULTS**

Mohamed Hani AbdElHamid Mohamed Tawfik ElMasry

Submitted in partial fulfilment of the requirements for the degree of  
Statistics and Information Management specialized in Risk  
Management and Analysis

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by

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**Supervisor: Professor Dr. Jorge Miguel Ventura Bravo**  
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## Abstract

To effectively manage credit score analysis, financial institutions instigated techniques and models that are mainly designed for the purpose of improving the process assessing creditworthiness during the credit evaluation process. The foremost objective is to discriminate their clients – borrowers – to fall either in the non-defaulter group, that is more likely to pay their financial obligations, or the defaulter one which has a higher probability of failing to pay their debts. In this paper, we devote to use machine learning models in the prediction of mortgage defaults. This study employs various single classification machine learning methodologies including Logistic Regression, Classification and Regression Trees, Random Forest, K-Nearest Neighbors, and Support Vector Machine. To further improve the predictive power, a meta-algorithm ensemble approach – stacking – will be introduced to combine the outputs – probabilities – of the afore mentioned methods. The sample for this study is solely based on the publicly provided dataset by Freddie Mac. By modelling this approach, we achieve an improvement in the model predictability performance. We then compare the performance of each model, and the meta-learner, by plotting the ROC Curve and computing the AUC rate. This study is an extension of various preceding studies that used different techniques to further enhance the model predictivity. Finally, our results are compared with work from different authors.

## Key words:

Credit Scoring, Machine Learning, Predictive Modelling, Stacking Ensemble, Freddie Mac, Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors, Support Vector Machine



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## Resumo

Para gerir com eficácia o risco de crédito, as instituições financeiras desenvolveram técnicas e modelos para melhorar o processo de avaliação da qualidade de crédito durante o processo de avaliação de propostas de crédito. O objetivo final é o de classificar os seus clientes - tomadores de empréstimos - entre aqueles que tem maior probabilidade de cumprir as suas obrigações financeiras, e os potenciais incumpridores que têm maior probabilidade de entrar em default. Nesta dissertação usamos diferentes metodologias de machine learning, incluindo Regressão Logística, Classification and Regression Trees, Random Forest, K-Nearest Neighbors, e Support Vector Machine na previsão do risco de default em crédito à habitação. Para melhorar o poder preditivo dos modelos, introduzimos a abordagem do conjunto de meta-algoritmos - stacking - para combinar as saídas - probabilidades - dos métodos acima mencionados. A amostra deste estudo é baseada exclusivamente no conjunto de dados fornecido publicamente pela Freddie Mac. Avaliamos em que medida a utilização destes modelos permite uma melhoria no desempenho preditivo. Em seguida, comparamos o desempenho de cada modelo e a stacking approach através da Curva ROC e do cálculo da AUC. Este estudo é uma extensão de vários estudos anteriores que usaram diferentes técnicas para melhorar a capacidade preditiva dos modelos.

### **Palavras-chave:**

Scoring de crédito, Machine Learning, Predictive Modelling, Stacking Ensemble, Freddie Mac, Regressão logística, Decision Tree, Random Forest, K-Nearest Neighbors, Support Vector Machine

## 1. Introduction

The critical role of the mortgage market in triggering the recent global financial crisis has led to a surge in policy interest, bank regulation and academic research in credit risk modeling. Encouraged by regulators, banks now devote significant resources in developing internal credit risk models to better quantify expected credit losses and to assign the mandatory economic capital. Rigorous credit risk analysis is not only of significance to lenders and banks but is also of paramount importance for sound economic policy making and regulation as it provides a good check on the “health” of a financial system and at large, the course of the economy (Chamboko & Bravo, 2016, 2018c).

One of the main practices of banking institutions is to lend money to their clients. According to Huffing Post, the widespread reasons for clients to borrow money is to finance their home purchases. Whilst these future home owners seek banks that provide them with the lowest interest rates, banks in return lend money to clients that are likely able to meet their financial obligations. For banks to be able to weight the risk of their prospective borrower being able to fulfill their repayments, they collect tremendous information both on the borrower, and the underlying property of the mortgage. The outcome of these gathered data is referred to Credit Scoring, a concept merged about 70 years ago with (Durand, 1941), which indicates the creditworthiness of loan applicants. These applicants are then ranked according to their credit score for the determination of their default probability and the subsequent classification into either non-defaulter applicant or defaulter one (Thomas, Edelman, & Crook, 2002). Banks then catalogue the gathered information to decide between lend or not certain amount of money (Banasik, Crook, & Thomas, 1999; Louzada, Cancho, Roman, & Leite, 2012; Marron, 2007).

(Hand D.J & Jacka S, 1998) stated that “the process of modelling creditworthiness by financial institutions is referred to as credit scoring”. Credit scoring is based on statistical or operational research methods. Historically, linear regression has been the most widely used techniques for building clients’ scorecards. A detailed instructions of credit scoring was presented by (Henly, 1995) including evaluation of previous published work on credit scoring and a review of discrimination and classification techniques.

The regulatory changes brought by the revised Basel Accords (subsequently adopted by national legislation in many countries and regions) introduced stronger risk management requirements for banks.

The main instruments of these regulations are the minimum capital requirements, the supervisory control mechanisms and the market discipline. Under this new regulation, the capital requirements are tightly coupled to estimated credit portfolio losses. According to the Basel II/III “internal ratings-based” (IRB) approach, financial institutions are allowed to use their own internal risk measures for key drivers of credit risk as key inputs in providing loss estimates for the mortgage book and in computing capital requirements (Basel, 2006; Chamboko & Bravo, 2018c). To assess the bank's credit risk exposure and provide appropriate loss estimates for the mortgage book, three risk measures are required: (i) the size of exposure at default, (ii) the probability of default and (iii) the loss given default.

The importance to manage risk has become more and more important recently as the percentage the Gross Domestic Product (a.k.a. GDP) rose from 40% to 130% (Mian and Sufi, 2014). GDP is a monetary measure of the market value of all the goods and services produced in a country, or a region, to estimate the economic performance of that country, and to make international comparisons. Since the 70s, regulators forced financial institutions to hold minimum capital requirements specified in the frameworks Basel I, Basel II, and Basel III (Debajyoti Ghosh Roy, Bindya Kohli, 2013), after which banks were motivated to adopt a forward-looking approach to determine credit risk. Nowadays, with the high availability of the enormous computational power, this approach or “Model” is based on Machine Learning methodologies. During the era afore the highly ranked computational systems and the introduction of machine learning, credit analysts used pure judgmental approach to accept or reject applicant’s form, which was tended to be based upon the view that what mattered was the 5Cs:

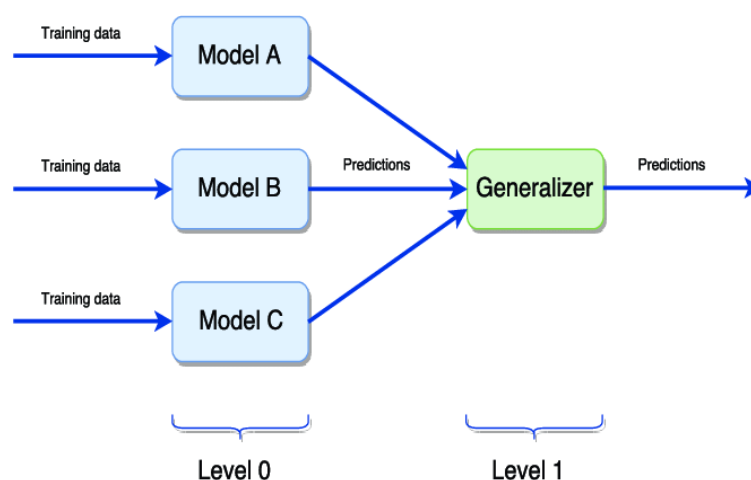
1. **The Character of the person** — do you know the person or their family?
2. **The Capital** — how much is being asked for?
3. **The Collateral** — what is the applicant willing to put up from their own resources?
4. **The Capacity** — what is their repaying ability. How much free income do they have?
5. **The Condition** — what are the conditions in the market?

Traditional credit scoring models applying single-period classification techniques (e.g., logit, probit) to classify credit customers into different risk groups and to estimate the probability of default are among the most popular data mining techniques used in the industry. Classical scoring models such as the logit regression can only provide an estimate of the lifetime probability of default for a loan but cannot identify the existence of cures and or other competing transitions and their relationship to loan-level and macro covariates, and do not provide insight on the timing of default, the cure from default, the time

since default and time to collateral repossession (Gaffney et al., 2014; Chamboko & Bravo, 2018a,b,c). Nowadays, with the revolution of big data and its uncontroversial positive effect, banking institutions use machine learning approach, which mainly refers to a set of algorithms designed to tackle computationally intensive pattern-recognition problems in extremely large datasets. The widely used ones are Bagging (Leo Breiman, 1996), Boosting (Schapire, Freund, Bartlett, & Lee, 1998), and recently Stacking (Wolpert, 1992). These are called Ensemble methods (Dumitrescu *et al.* 2018).

Bagging and Boosting aim at improving the predictive power of machine learning algorithms by using a linear combination of predictions from many variants of this algorithm, through averaging or majority vote, rather than individual model. Bagging is the application of the Bootstrap (Efron & Tibshirani, 1993) procedure to a high-variance machine learning algorithm, typically decision trees. Boosting uses an iterative method, where it mainly learns from individuals that were misclassified in previous iterations by giving them more weight so that in the next iteration the learner would focus more on them. We will not dig any deeper in Bagging or Boosting in this paper, as we will be more focused on the Stacking technique. For a review of Bagging and Boosting methods see (Bühlmann, 2012; Hastie, Tibshirani, & Friedman, 2001). Stacking introduces the concept of Meta Learner. Unlike bagging and boosting, stacking combine models of different types. An output of level 0 classifier will be used as an input of level 1 classifier to approximate the same target function. Figure 1 shows a simple demonstration of stacking ensemble.

*Figure 1: Stacking Ensemble*



**Source:** ResearchGate.

## **1.1. Purpose**

The novelty of this paper lies in making use of stacking ensemble (Smyth & Wolpert, 1998; Wolpert, 1992) in predicting the mortgage default. We use machine learning methods, such as Linear Discriminate Analysis (LDA), Classification and Regression Trees (CART), Random Forest (RM), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) as a level 0 classifier and use the output as an input to Logistic Regression (LR) model. We shall examine and compare the output with a single classifier output of the same level 1 model, logistic regression, via AUC and ROC curve. In this thesis, we are using a data set provided by Freddie Mac. Freddie Mac is a government-sponsored enterprise that plays a central role in the US housing finance system and at the start of their conservatorships held or guaranteed about \$5.2 trillion of home mortgage debt. The firm was often cited as a shining example of public-private partnerships—that is, the harnessing of private capital to advance the social goal of expanding homeownership (Frame, Fuster, Tracy, & Vickery, 2015).

## **1.2. Thesis Outline**

The first section of the paper will introduce the credit risk modelling and highlight some of the techniques previously used and wide grow of the data presence, which led to surfacing of the statistical techniques. The second section will be the literature review and the model presentation. In the third section, we will focus on the methodology used for the data preparation, where we will discuss “mice” for missing data imputation, some feature selection techniques, and Stacking Ensemble. The third section will also discuss the modelling technique that will be applied on the data. It is worthy to mention that R-Studio was used throughout the entire pre-processing and modelling stages. The fourth section will explore our dataset and highlight the relationship between the default rate and the available variables. The fifth section will be applying the models to our dataset. The sixth section will highlight all the outputs and discuss the accuracy of each model. The sixth and the final section will conclude our work.

## **2. Literature Review**

In this section, we provide a brief lookback on previous studies by various authors, we well as some of their remarkable results.

### **2.1. A Glimpse from Parallel Studies**

There are many studies developed, and still developing, in this subject. Various methodologies and approaches were applied to increase the predictive power and the output accuracy level with the least overfitting issue, yet, many models and methodologies remain uncovered and assorted questions remain to be answered. (AlAmari, 2002) highlighted some of the questions regarding the optimal methods for customer evaluations and the variables – features – that a credit analyst should include in assessing a borrower's application. He also extended his argument with more questions like “What is the best statistical technique on the basis of the highest average correct classification rate or lowest misclassification cost or other evaluation criteria?”. Some modelling cases follow around studies on this area, (Hand, 2005) for example, used latent-variable technique to split the clients' physiognomies into primary characteristics (X) and behavioral characteristics (Y). Then the study summarizes them into overall measure of credit consumer scores. Early research focused on determining the major factors in determining default rates rather than building a predictive model to discriminate between the good client and the bad one (non-defaulter and defaulter respectively). For example, (Vandell, 1978) hypothesis stated that the ratio of loan value to the property value are the foremost variable.

Although application of machine learning in Finance is relatively new concept, yet, much research has been conducted in that area. (Khandani, Kim, & Lo, 2010), (Butaru et al., 2016), (Fitzpatrick & Mues, 2016), (Jafar Hamid & Ahmed, 2016), (I. Brown & Mues, 2012), (Bolarinwa, 2017) and (Sealand, 2018) employed machine learning in predicting loan default. Some of these studies used small datasets with several thousand mortgages, while other used dataset of millions of mortgages. Models used include logistic regression (single and multinomial), Naïve Bayes, Random Forest, Ensemble (Y. W. Zhou, Zhong & Li, 2012)<sup>1</sup>, K-Nearest Neighborhood and Survival Analysis (Bellotti & Crook, 2009).

In (Bolarinwa, 2017) research, random forest performed extremely well with an accuracy of 95.68%, and Naïve Bayes had the lowest accuracy of 70.74%. Worth mentioning that most published studies compiled data from different sources such as employment rates and rent ratio data. (Sealand, 2018) summarized the results from the top research studies carried that highlighted an AUC output of 99.42%, 95.64%, and 92.92% for (I. Brown & Mues, 2012), (Bolarinwa, 2017), and (Deng, 2016) respectively. (Groot, 2016), (Deng, 2016), (Sealand, 2018) and (Bolarinwa, 2017) used either data from Freddie Mac, or Fennie Mae.

When applying these machine learning techniques, all research followed (Koh, Tan & Goh, 2006) illustration of the use of data mining techniques, the suggested model has five steps: defining the objective, selecting variables, selecting sample and collecting data, selecting modelling tools and constructing models, validating and assessing models. Feature reduction was another technique introduced in the financial world by (Azam, Danish & Akbar, 2012) who evaluated the significance of loan applicant socioeconomic attributes on personal loan decision in banks using descriptive statistics and logistic regression, which identified that out of six independent variables only three variables (region, residence status and year with the current organization) have significant impact on personal loan decision.

## **2.2. Results from Related Work**

Results from related previous work, such as that of (Addo, Guegan, & Hassani, 2018), (Tokpavi, 2018), (Bagherpour, 2017), (GROOT, 2016), (Horn, 2016), (Mamonov & Benbunan-Fich, 2017), (Bolarinwa, 2017), (Deng, 2016), and (D. R. Brown, 2012) are included in Table 1.

*Table 1: Results from Related Work*

<b>Author</b>	<b>Model</b>	<b>Accuracy</b>
<b>(Addo et al., 2018)</b>	Logistic Regression	0.876280
	Random Forest	0.993066
	Boosting Technique	0.994803
<b>(Tokpavi, 2018)</b>	Linear Logistic Regression	0.6982
	Non-Linear Logistic Regression	0.7648
	MARS	0.8570
	Random Forest	0.8386
	PLTR	0.8519
<b>(Bagherpour, 2017)</b>	Logistic Regression	0.85
	KNN	0.87
	Radom Forest	0.87
	Support Vector Machine	0.86
	Factorization Machines	0.88
<b>(GROOT, 2016)</b>	Weighted Support Vector Machine	0.774
<b>(Horn, 2016)</b>	Genetic Programming	0.777
	Support Vector Machine	0.756
	Boosted Trees	0.779
<b>(Mamonov &amp; Benbunan-Fich, 2017)</b>	Logistic Regression	0.599
	Decision Tree	0.665
	Random Forest	0.665
	Boosted Trees	0.692
	Support Vector Machine	0.593
	Neural Networks	0.594
<b>(Bolarinwa, 2017)</b>	Logistic Regression	0.9515
	Matrix Naïve Bayes	0.7074
	Random Forest	0.9564
	K-Nearest Neighbors	0.8314
<b>(Deng, 2016)</b>	Logistic Regression	0.9738
	K-Nearest Neighbors	0.7815
	Random Forest	0.9292
<b>(D. R. Brown, 2012)</b>	Classification Trees	0.8209
	Support Vector Machines	0.8383
	Genetic Programming	0.9943

**Source:** Authors preparation.



### 3. Models Presentation

In this section we aim to present the differences between the Ensemble techniques and discuss the prediction models used in our study.

#### 3.1. Ensemble

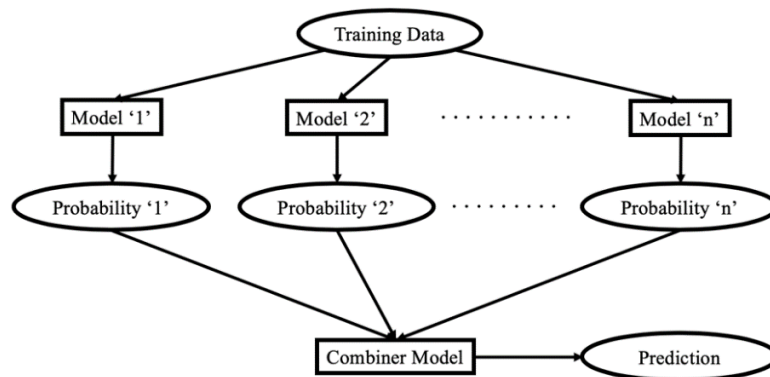
Ensemble methods that train multiple learners (the learned model can be called a hypothesis) and then combine them for use, with Boosting and Bagging as representatives, are a kind of state-of-the art learning approach. Ensemble methods train multiple learners to solve the same problem.

Contrary to ordinary learning approaches which try to construct one learner from training data, ensemble methods try to construct a set of learners and combine them. Ensemble learning is also called committee-based learning, or learning multiple classifier systems (Z.-H. Zhou, 2012). Ensemble is merely a technique that boost the accuracy of weak learners (also referred to as base learners) to strong learners, which can make very accurate predictions. It combines two or more algorithms of similar or dissimilar types called base learners. This makes a more robust system, which incorporates the predictions from all the base learners to get our final “accurate” and less likely biased decision. Figure 2 shows a common ensemble architecture.

There are three threads of early contributions that led to the current area of ensemble methods; that is, **combining classifiers**, **ensembles of weak learners** and **mixture of experts**.

- **Combining classifiers** was mostly studied in the pattern recognition community. Researchers in this thread generally work on strong classifiers and try to design powerful combining rules to get stronger combined classifiers.
- **Ensembles of weak learners** was mostly studied in the machine learning community. Researches in this field often work on weak learners and try to design powerful algorithms to boost the performance from weak to strong.
- **Mixture of experts** was mostly studied in the neural networks’ community. Researchers generally consider a divide-and-conquer strategy, try to learn a mixture of parametric models jointly and use combining rules to get an overall solution.

Figure 2: A common ensemble architecture



Source: Authors preparation.

The two basic concepts of ensemble are as follows:

- **Averaging** — Simple averaging obtains the combined output by averaging the outputs of individual learners directly. Table 2 illustrates and example.

Table 2: Averaging Example

Model 01	Model 02	Model 03	<b>Average</b>
130	80	90	<b>100</b>

Source: Authors preparation.

- **Majority Vote** — It's defined as taking the prediction with maximum vote / recommendation from multiple models' predictions while predicting the outcomes of a classification problem. Table 3 illustrates and example.

Table 3: Voting Example

Model 01	Model 02	Model 03	<b>Vote</b>
1	0	1	<b>1</b>

Source: Authors preparation.

Other concepts include **Weighted Averaging**, **Plurality Voting**, **Weighted Voting**, and **Soft Voting**, which was further explored by (Z.-H. Zhou, 2012).

## **Boosting and Bagging**

There are two paradigms of ensemble methods, that is, sequential ensemble methods, where the base learners are generated sequentially, with Boosting as a representative, and parallel ensemble methods where the base learners are generated in parallel, with Bagging as a representative.

The basic motivation of sequential methods is to exploit the dependence between the base learners, since the overall performance can be boosted in a residual-decreasing way. Meanwhile, the basic motivation of parallel ensemble methods is to exploit the independence between the base learners, since the error can be reduced dramatically by combining independent base learners.

### **Boosting**

Boosting refers to boosting performance of weak models. It involves the first algorithm is trained on the entire training data and the subsequent algorithms are built by fitting the residuals of the first algorithm, thus giving higher weight to those observations that were poorly predicted by the previous model.

*Figure 3:A general boosting procedure*

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**Input:** Sample distribution  $\mathcal{D}$ ;  
Base learning algorithm  $\mathfrak{L}$ ;  
Number of learning rounds  $T$ .

**Process:**

1.  $\mathcal{D}_1 = \mathcal{D}$ .     % Initialize distribution
2. **for**  $t = 1, \dots, T$ :
3.      $h_t = \mathfrak{L}(\mathcal{D}_t)$ ;     % Train a weak learner from distribution  $\mathcal{D}_t$
4.      $\epsilon_t = P_{\mathbf{x} \sim \mathcal{D}_t}(h_t(\mathbf{x}) \neq f(\mathbf{x}))$ ;     % Evaluate the error of  $h_t$
5.      $\mathcal{D}_{t+1} = \text{Adjust\_Distribution}(\mathcal{D}_t, \epsilon_t)$
6. **end**

**Output:**  $H(\mathbf{x}) = \text{Combine\_Outputs}(\{h_1(\mathbf{x}), \dots, h_t(\mathbf{x})\})$

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**Source:** Ensemble Methods Foundations and Algorithms (Z.-H. Zhou, 2012).

The general boosting procedure is quite simple. Suppose the weak learner will work on any data distribution it is given and take the binary classification task as an example; that is, we are trying to classify instances as positive and negative. The training instances in space  $X$  are drawn i.i.d. from distribution  $D$ , and the ground-truth function is ‘ $f$ ’. Suppose the space  $X$  is composed of three parts  $X_1$ ,  $X_2$  and  $X_3$ , each takes 1/3 amount of the distribution, and a learner working by random guess has 50%

classification error on this problem. We want to get an accurate (e.g., zero error) classifier on the problem, but we are unlucky and only have a weak classifier at hand, which only has correct classifications in spaces  $X_1$  and  $X_2$  and has wrong classifications in  $X_3$ , thus has  $1/3$  classification error. Let's denote this weak classifier as  $h_1$ . It is obvious that  $h_1$  is not desired.

The idea of boosting is to correct the mistakes made by  $h_1$ . We can try to derive a new distribution  $D'$  from  $D$ , which makes the mistakes of  $h_1$  more evident, e.g., it focuses more on the instances in  $X_3$ . Then, we can train a classifier  $h_2$  from  $D'$ . Again, suppose we are unlucky and  $h_2$  is also a weak classifier, which has corrected classifications in  $X_1$  and  $X_3$  and has wrong classifications in  $X_2$ . By combining  $h_1$  and  $h_2$  in an appropriate way, the combined classifier will have correct classifications in  $X_1$ , and maybe some errors in  $X_2$  and  $X_3$ . Again, we derive a new distribution  $D''$  to make the mistakes of the combined classifier more evident, and train a classifier  $h_3$  from the distribution, so that  $h_3$  has correct classifications in  $X_2$  and  $X_3$ . Then, by combining  $h_1$ ,  $h_2$  and  $h_3$ , we have a perfect classifier, since in each space of  $X_1$ ,  $X_2$  and  $X_3$ , at least two classifiers make correct classifications.

## Bagging

It is also called Bootstrap Aggregating. In this algorithm, it creates multiple models using the same algorithm but with random sub-samples of the dataset which are drawn from the original dataset randomly with random with replacement sampling technique (i.e. bootstrapping). This sampling method simply means some observations appear more than once while sampling.

*Figure 4: The Bagging algorithm*

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**Input:** Data set  $D = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_m, y_m)\}$ ;  
Base learning algorithm  $\mathcal{L}$ ;  
Number of base learners  $T$ .

**Process:**

1. **for**  $t = 1, \dots, T$ :
2.  $h_t = \mathcal{L}(D, \mathcal{D}_{bs})$  %  $\mathcal{D}_{bs}$  is the bootstrap distribution
3. **end**

**Output:**  $H(\mathbf{x}) = \arg \max_{y \in \mathcal{Y}} \sum_{t=1}^T \mathbb{I}(h_t(\mathbf{x}) = y)$

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**Source:** Ensemble Methods Foundations and Algorithms (Z.-H. Zhou, 2012).

After fitting several models on different samples, these models are aggregated by using their average, weighted average or a voting method.

The bagging and boosting algorithms are suitable means to increase efficiency of a classification algorithms, however, the loss of simplicity of this classification scheme can be regarded as a disadvantage (Machova, Puszta, Barcak, & Bednar, 2006).

### 3.1.1. Stacking

Stacking is a technique where a learner is trained to combine the individual learners. In stacking, the individual learners are called the *first-level learners*, whereas the combiner is called the *second-level learner*, or *meta-learner*. We first train the first-level learners using the original training data set, and then generate a new data set for training the meta-learner, where the outputs of the first-level learners are regarded as input features while the original labels are still regarded as labels of the new training data. Figure 5 demonstrates a general stacking procedure.

Figure 5: A General Stacking procedure

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<b>Input:</b>	Data set $D = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_m, y_m)\}$ ; First-level learning algorithms $\mathcal{L}_1, \dots, \mathcal{L}_T$ ; Second-level learning algorithm $\mathcal{L}$ .
<b>Process:</b>	
1.	<b>for</b> $t = 1, \dots, T$ :    % Train a first-level learner by applying the
2.	$h_t = \mathcal{L}_t(D)$ ;    % first-level learning algorithm $\mathcal{L}_t$
3.	<b>end</b>
4.	$D' = \emptyset$ ;    % Generate a new data set
5.	<b>for</b> $i = 1, \dots, m$ :
6.	<b>for</b> $t = 1, \dots, T$ :
7.	$z_{it} = h_t(\mathbf{x}_i)$ ;
8.	<b>end</b>
9.	$D' = D' \cup ((z_{i1}, \dots, z_{iT}), y_i)$ ;
10.	<b>end</b>
11.	$h' = \mathcal{L}(D')$ ;    % Train the second-level learner $h'$ by applying % the second-level learning algorithm $\mathcal{L}$ to the % new data set $D'$ .
<b>Output:</b>	$H(\mathbf{x}) = h'(h_1(\mathbf{x}), \dots, h_T(\mathbf{x}))$

---

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**Source:** Ensemble Methods Foundations and Algorithms (Z.-H. Zhou, 2012).

In the training phase of stacking, a new data set needs to be generated from the first-level classifiers. If the exact data that are used to train the first-level learner are also used to generate the new data set for

training the second-level learner, there will be a high risk of overfitting. Hence, it is suggested that the instances used for generating the new data set are excluded from the training examples for the first-level learners, and a cross-validation or leave-one-out procedure is often recommended.

Generally stacking proved success in many different applications. (Leo Breiman, 1996) demonstrated the success of stacked regression, where he used linear regression models with different numbers of variables as the first-level learners, and least-square linear regression model as the second-level learner under the constraint that all regression coefficients are non-negative. This non-negativity constraint was found to be crucial to guarantee that the performance of the stacked ensemble would be better than selecting the single best learner.

Since many previous studies were conducted using Boosting and Bagging, in our paper we will be implementing stacking ensemble technique to fit our model.

### **3.2. Prediction Models**

In this section, we will briefly explore the prediction models used in this paper. Models explored include Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors, and Support Vector Machine.

#### **3.2.1. Logistic Regression**

Logistic Regression model (Cox, 1958) is a statistical method utilized in machine learning to assess the relationship between a dependent categorical variable (output) and one or more independent variables (predictors) by employing a logistic function to evaluate the probabilities. Logistic Regression can be binary (output variable has two classes), multinomial (output variable has more than two classes) or ordinal (Bolarinwa, 2017). In our study we only use the linear output as we are only discriminate between default and non-default loans.

The logistic function is given by formula (1):

$$f(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}} \quad (1)$$

where  $f(x)$ , in this scope, represents the probability of an output variable (two classes: 0 or 1),  $\beta_0$  is the linear regression intercept and  $\beta_1$  is the multiplication of the regression coefficient by  $x$  value of the independent variable. In our application, the output variable with the value 1 represents the probability of loan status being default and 0 is the probability of loan status equaling paying. This information can be represented in a form of a logistic equation as shown in formula (2):

$$P = P(\text{loan default status} = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x + \dots + \beta_k x_k)}} \quad (2)$$

where  $k$  is the number of independent variables. Therefore, the logistic regression formula for default loans becomes:

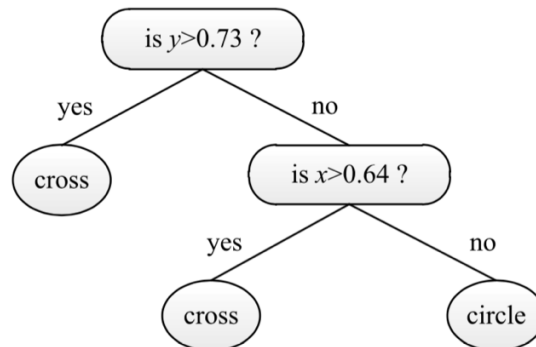
$$\frac{f(x)}{1 - f(x)} = e^{-(\beta_0 + \beta_1 x + \dots + \beta_k x_k)} \quad (3)$$

Concluding that the formula for non-default loans will simply be  $1-p$ .

### 3.2.2. Decision Tree

Classification and regression trees (CART) are used for constructing prediction models from data. The models are obtained by recursively partitioning the data space and fitting a simple prediction model within each partition. As a result, the partitioning can be represented graphically as a decision tree. Classification trees are designed for dependent variables that take a finite number of unordered values, with prediction error measured in terms of misclassification cost. Regression trees are for dependent variables that take continuous or ordered discrete values, with prediction error typically measured by the squared difference between the observed and predicted values (Leo Breiman, 2001; Loh, 2014).

Figure 6: Simple example of a decision tree



**Source:** Ensemble Methods Foundations and Algorithms (Z.-H. Zhou, 2012).

One problem with decision trees is that features with a lot of possible values will be favored, ignoring their relevance to classification. The information gain split would be quite large in this case. This is where C4.5 algorithm (Quinlan, 1992) was introduced. This introduction addressed the information gain criterion by employing gain ratios, which is simply a variant of the information gain criterion, taking normalization on the number of feature values. In real-life, the feature with the highest gain ratio is selected as the split. Cart (L Breiman, Friedman, Olshen & Stone, 1984) is another famous decision tree algorithm, which uses Gini index for selecting the split.

### 3.2.3. Random Forest

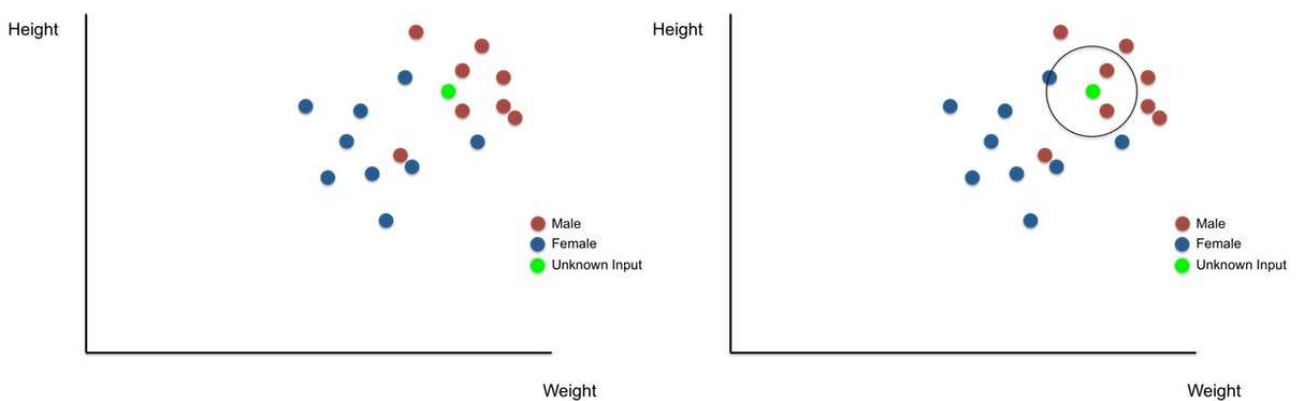
Random Forest (Leo Breiman, 2001; Ho, 1995) model is used for performing classification or regression tasks. This is achieved by constructing several decision trees and then giving as output the class that is the most occurring (mode) of the classes for classification and mean prediction for regression tasks. In this section we focus on random forest for classification tasks. Random forest models make use of random selection of features in splitting the decision trees, hence the classifier built from this model is made up of a set of tree-structured classifiers. The random forest has a major advantage that it can be used to judge variable importance by ranking the performance of each variable. The model achieves this by estimating the predictive value of variables and then scrambling the variables to examine how much the performance of the model drops (Bolarinwa, 2017).



### 3.2.4. K-Nearest Neighbors (KNN)

It is called Lazy Learner. It is called lazy not because of its apparent simplicity, but because it doesn't learn a discriminative function from the training data but memorizes the training dataset instead. The K-Nearest Neighbor classifier (Altman, 1992) is an example of a non-parametric statistical model, hence it makes no explicit assumptions about the form and the distribution of the parameters. KNN is a distance-based algorithm, taking majority vote between the 'k' closest observations. Distance metrics employed in KNN model includes for example Euclidean, Manhattan, Chebyshev and Hamming distance. For the sake of illustration, a K-Nearest Neighbor learner identifies the 'k' instances from the training set that are closest to the test instance. Then, for classification, the test instance will be classified to the majority class among the 'k' instances; while for regression, the test instance will be assigned the average value of the  $k$  instances.

*Figure 7: Illustrates how to classify an instance by a 3-nearest neighbor classifier*



Source: Brilliant.

### 3.2.5. Support Vector Machine (SVM)

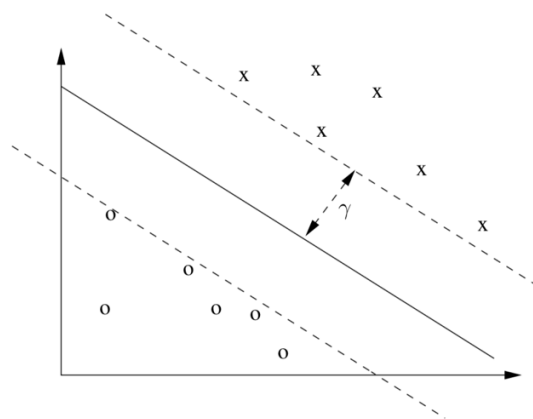
Support Vector Machines (Cortes & Vapnik, 1995) are one of the best learning algorithms for classification and regressions. The SVM finds a hyper-plane that separates training observations to maximize the margin (smallest vertical distance between observations and the hyper-plane). Intuitively, there are many hyper-planes that can separate the classes and each of them has a certain margin. The distance between observations and the decision boundary explains how sure about prediction. If one observation is in longer distance with hyper-plane, more probably it belongs to the correct classes. Therefore, an optimal hyper-plane maximizes the margin. This optimal hyper-plane is determined based

on observations within the margin which are called support vectors. Therefore, the observations outside of support vectors don't influence the hyper-plane (Bagherpour, 2017).

The idea behind SVM's is that of mapping the original data into a new, high-dimensional space, where it is possible to apply linear models to obtain a separating hyper-plane, for instance, separating the classes of the problem, in the case of classification tasks. The mapping of the original data into this new space is carried out with the help of the so-called kernel functions. SVMs are linear machines operating on this dual representation induced by kernel functions.

The hyper-plane separation in the new dual representation is frequently done by maximizing a separation margin between cases belonging to different classes; see Figure 8. This is an optimization problem often solved with quadratic programming methods. Soft margin methods allow for a small proportion of cases to be on the "wrong" side of the margin, each of these leading to a certain "cost".

*Figure 8: The margin maximization in SVMs*



**Source:** Data Mining with R Learning with Case Studies (Torgo, 2016).

### **3.2.6. Multiple Imputation by Chained Equations (MICE)**

MICE is one of the most commonly used methods to impute missing values in datasets. It creates a separate model for each incomplete variable, i.e. it imputes data on a variable by variable basis by specifying an imputation model per variable. Further details about MICE were published by (Buuren & Groothuis-Oudshoorn, 2011).

### 3.3. Evaluation Criteria

Various performance evaluation criteria are used in credit scoring applications. According to (Lessmann, Baesens, Seow & Thomas, 2015), most studies rely on a single performance measure, which is split into three types; illustrated in figure 10:

Figure 9: Three Types of Performance Measure

<b>Discriminatory ability</b>	<ul style="list-style-type: none"> <li>- Area under the curve (AUC)</li> <li>- Partial Gini Index (PG)</li> <li>- H-Measure</li> </ul>
<b>Accuracy of probability predictions</b>	<ul style="list-style-type: none"> <li>- Brier-Score (BS)</li> </ul>
<b>Correctness of predictions</b>	<ul style="list-style-type: none"> <li>- Kolmogorov-Smirnov Statistics (KS)</li> <li>- Percent Correctly Classified (PCC)</li> </ul>

**Source:** Authors preparation.

The PCC and KS assess the correctness of categorical predictions. Table 4 briefly explains the Correctness of Predictions Performance Measure.

#### Correctness of predictions

Table 4: Correctness of Predictions Performance Measure

<b>Percent Correctly Classified (PCC)</b>	The <i>PCC</i> is the portion the observations that are classified correctly. It necessitates separate class predictions, which is obtained by comparing $p(+ x)$ to a threshold ' $\tau$ ' and assigning ' $x$ ' to the positive class if $p(+ x) > \tau$ , and assigning ' $x$ ' to the negative class if $p(+ x) < \tau$ . In practice, ' $\tau$ ' depends on the costs associated with granting credit to bad – defaulting – customers or rejecting good – non-defaulting – customers (Hand, 2005).
<b>Kolmogorov-Smirnov Statistics (KS)</b>	KS is based on $p(+ x)$ but considers a fixed reference point. <i>KS</i> is mainly the maximum difference between the cumulative score distributions of positive and negative cases (Thomas et al., 2002).

**Source:** Authors preparation.

Both *PCC* and *KS* embody measure accuracy comparative to a single reference point (' $\tau$ ' or the KS point).

## Accuracy of probability predictions

Table 5: Accuracy of Probability Predictions Performance Measure

<b>Brier-Score (BS)</b>	<i>BS</i> is the mean-squared error between $p(+ x)$ and a zero-one response variable (Hernandez-Orallo, Flach, & Ferri, 2011).  The <i>BS</i> performs a global assessment, in that it considers the whole score distribution. It considers absolute score values.
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Source: Authors preparation.

The AUC, H-measure, and PG assess discriminatory ability, and the BS assesses the accuracy of probability predictions. Table 6 briefly describes the Discriminatory Ability Performance Measure.

## Discriminatory ability

Table 6: Discriminatory Ability Performance Measure

<b>Area under the curve (AUC)</b>	The <i>AUC</i> equals the probability that a randomly chosen positive case receives a score higher than a randomly chosen negative case.  The <i>AUC</i> performs a global assessment, in that it considers the whole score distribution. It uses relative (to other observations) score ranks.
<b>H-Measure</b>	The H-measure gives a normalized classifier assessment based on expected minimum misclassification loss; ranging from zero (random classifier) to one (perfect classifier).
<b>Partial Gini Index (PG)</b>	The <i>PG</i> concentrates on one part of the score distribution $p(+ x) \leq b$ (Pundir & Seshadri, 2012).

Source: Authors preparation.

Expanding on the AUC technique; the AUC test is based on so called ROC (Receiver Operator Characteristics) curves. It merely measures the performance of binary classification functions, which are functions that classify elements as positive or negative. If, for instance, an observation is classified into

the positive class, and indeed belongs to the positive class, then we call it a true positive. On the other hand, if the observation is classified as true positive, while it is negative, then we call it false positive. In the same way we have true negative and false negative. Table 7 illustrates the contingency table of binary classification.

*Table 7:Contingency table of binary classification*

	<b>Predicted Condition = Positive 1</b>	<b>Predicted Condition = Negative 0</b>
<b>True Condition = Positive 1</b>	<b>True Positive - TP</b> (correctly predicted a true condition)	<b>False Negative - FN</b> (wrongly predicted a negative condition)
<b>True Condition = Negative 0</b>	<b>False Positive - FP</b> (wrongly predicted a true condition)	<b>True Negative – TN</b> (correctly predicted a negative condition)

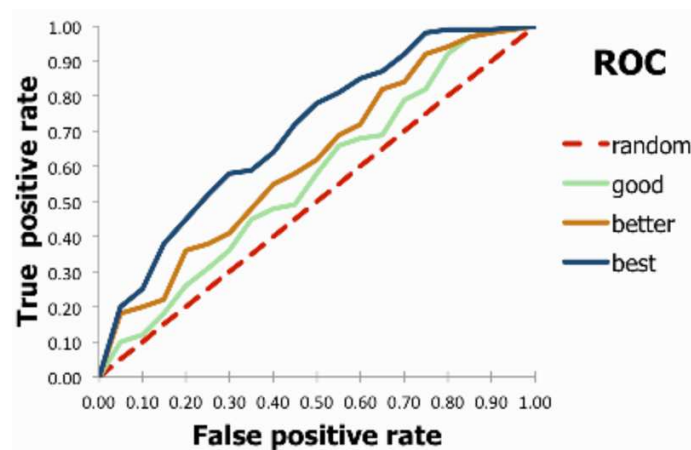
**Source:** Authors preparation.

## Plotting the ROC Curve

ROC space is defined by FPR and TPR as 'x' and 'y' axes respectively, which depicts relative trade-offs between true positive (benefits) and false positive (costs). The best possible prediction method would yield a point in the upper left corner or coordinate (0,1) of the ROC space, representing 100% sensitivity (no false negatives) and 100% specificity (no false positives). The (0,1) point is also called a perfect classification. A completely random guess would give a point along a diagonal line (the so-called line of no-discrimination) from the left bottom to the top right corners (regardless of the positive and negative base rates). An intuitive example of random guessing is a decision by flipping coins (heads or tails). As the size of the sample increases, a random classifier's ROC point migrates towards (0.5,0.5).

The diagonal divides the ROC space. Points above the diagonal represent good classification results (better than random), points below the line represent poor results (worse than random).

*Graph 1: ROC Space*



Source: OpenEye Scientific.

Given that there is imbalance shown in the class distributions in our data (see section 4.4), it is important to reason whether and how class skew affects the performance measures. The *AUC*, *PG*, and *H*-measure are not affected by class imbalance (Fawcett, 2005), however, the *BS* and the *KS* are affected by class imbalance as they are based on the score distribution of a classifier, i.e. *BS* and *KS* are robust toward class skew (Gong & Huang, 2012). For this reason, in our project we consider the performance measure of *AUC* by plotting the ROC Curve a viable approach for classifier comparisons, highlighting the model's accuracy.

## **4. Dataset Properties**

In this section we present the data set used in our paper, which is publicly provided by Freddie Mac. The dataset covers approximately 25.7 million fixed-rate mortgages originated between January 1, 1999 and March 31, 2017. Monthly loan performance data, including credit performance information up to and including property disposition, is being disclosed through September 30, 2017 (Freddie Mac Overview, 2018). Working on “Big” data, such as the one provided here, is quite a challenge given that it does not only require a high-pitched computational power, but also most of the regular programs don’t have the necessary capability to process such information. An unpretentious definition of Big Data is data that is big in Volume, i.e. Tall and Wide Data. Various tools were introduced such as H2O Library, which uses in-memory compression to handle billions of data even with a small cluster (Bash, 2015). Although this state-of-art library is very promising dealing with our dataset, yet R-Studio still needs to load the dataset onto the computer memory, which would not be currently sufficient. That said, we instead proceeded with using Freddie Mac’s sample data, also available publicly on their website, which consists on random samples of 50,000 loans selected from each full year. On these samples the website guarantees the proportional number of loans from each partial year of the full Single-Family Loan-Level Dataset.

The Dataset includes two sets of files, Loan-level origination files, and monthly loan performance on a portion of the fully amortizing 30-year fixed-rate Single Family mortgages that Freddie Mac acquired with origination dates from 1999 to the Origination Cut-off Date. The Loan-Level origination file contain information for each loan at the time of origination and Monthly Loan Performance Files contain corresponding monthly performance data. That said, we have an eye on the loans that were approved only, and not the ones that clients applied for, but their loans never went through.

### **4.1. Data Dictionary**

In this section, we provide information regarding the layout of each file, origination and monthly performance, that are available publicly on the website of Freddie Mac, in addition to information about each data elements contained within each file type.

#### 4.1.1. Origination Data

Table 8: Origination File, Data Dictionary

#	Origination Variable	Description	Allowable Values
1	fico	<b>CREDIT SCORE</b> - A number, prepared by third parties, summarizing the borrower's creditworthiness, which may be indicative of the likelihood that the borrower will timely repay future obligations. Generally, the credit score disclosed is the score known at the time of acquisition and is the score used to originate the mortgage.	301 - 850 9999 = Not Available, if Credit Score is < 301 or > 850.
2	dt_first_pi	<b>FIRST PAYMENT DATE</b> - The date of the first scheduled mortgage payment due under the terms of the mortgage note.	YYYYMM
3	flag_fthb	<b>FIRST TIME HOMEBUYER FLAG</b> - Indicates whether the Borrower, or one of a group of Borrowers, is an individual who (1) is purchasing the mortgaged property, (2) will reside in the mortgaged property as a primary residence and (3) had no ownership interest (sole or joint) in a residential property during the three-year period preceding the date of the purchase of the mortgaged property. With certain limited exceptions, a displaced homemaker or single parent may also be considered a First-Time Homebuyer if the individual had no ownership interest in a residential property during the preceding three-year period other than an ownership interest in the marital residence with a spouse. Investment Properties, Second Homes and Refinance transactions are not eligible to be considered First-Time Homebuyer transactions. Therefore, First Time Homebuyer does not apply and will be disclosed as "Not Applicable", which will be indicated by a blank space.	Y = Yes N=No 9 = Not Available or Not Applicable
4	dt_matr	<b>MATURITY DATE</b> - The month in which the final monthly payment on the mortgage is scheduled to be made as stated on the original mortgage note.	YYYYMM
5	cd_msa	<b>METROPOLITAN STATISTICAL AREA (MSA) OR METROPOLITAN DIVISION</b> - This disclosure will be based on the designation of the Metropolitan Statistical Area or Metropolitan Division based on 2010 census (for Mar 2013 and May 2013 releases) and 2013 census (for Aug 2013 and Dec 2013 releases) data. Metropolitan Statistical Areas (MSAs) are defined by the United States Office of Management and Budget (OMB) and have at least one urbanized area with a population of 50,000 or more inhabitants. OMB refers to an MSA containing a single core with a population of 2.5 million or more, which may be comprised of groupings of counties, as a Metropolitan Division. If an MSA applies to a mortgaged property, the applicable five-digit value is disclosed; however, if the mortgaged property also falls within a Metropolitan Division classification, the applicable five-digit value for the Metropolitan Division takes precedence and is disclosed instead. Changes and/or updates in designations of MSAs or Metropolitan Division will not be reflected in the Single-Family Historical Dataset.	Metropolitan Division or MSA Code. Space (5) = Indicates that the area in which the mortgaged property is located is a) neither an MSA nor a Metropolitan Division, or b) unknown.
6	mi_pct	<b>MORTGAGE INSURANCE PERCENTAGE (MI %)</b> - The percentage of loss coverage on the loan, at the time of Freddie Mac's purchase of the mortgage loan that a mortgage insurer is providing to cover losses incurred as a result of a default on the loan. Only primary mortgage insurance that is purchased by the Borrower, lender or Freddie Mac is disclosed. Mortgage insurance that constitutes "credit enhancement" that is not required by Freddie Mac's Charter is not disclosed. Amounts of mortgage insurance reported by Sellers that are less than 1% or greater than 55% will be disclosed as "Not Available," which will be indicated 999. No MI will be indicated by three zeros.	1%-55% 000= NoMI 999 = Not Available
7	cnt_units	<b>NUMBER OF UNITS</b> - Denotes whether the mortgage is a one-, two-, three-, or four-unit property.	1 = one-unit 2 = two-unit 3 = three-unit 4 = four-unit 99 = Not Available
8	occpy_sts	<b>OCCUPANCY STATUS</b> - Denotes whether the mortgage type is owner occupied, second home, or investment property.	P = Primary Residence I = Investment Property S = Second Home 9 = Not Available
9	cltv	<b>ORIGINAL COMBINED LOAN-TO-VALUE (CLTV)</b> - In the case of a purchase mortgage loan, the ratio is obtained by dividing the original mortgage loan amount on the note date plus any secondary mortgage loan amount disclosed by the Seller by the lesser of	0% - 200% 999 = Not Available



		<p>the mortgaged property's appraised value on the note date or its purchase price. In the case of a refinance mortgage loan, the ratio is obtained by dividing the original mortgage loan amount on the note date plus any secondary mortgage loan amount disclosed by the Seller by the mortgaged property's appraised value on the note date. If the secondary financing amount disclosed by the Seller includes a home equity line of credit, then the CLTV calculation reflects the disbursed amount at closing of the first lien mortgage loan, not the maximum loan amount available under the home equity line of credit. In the case of a seasoned mortgage loan, if the Seller cannot warrant that the value of the mortgaged property has not declined since the note date, Freddie Mac requires that the Seller must provide a new appraisal value, which is used in the CLTV calculation. In certain cases, where the Seller delivered a loan to Freddie Mac with a special code indicating additional secondary mortgage loan amounts, those amounts may have been included in the CLTV calculation.</p> <p>If the LTV is &lt; 80 or &gt; 200 or Not Available, set the CLTV to 'Not Available.' If the CLTV is &lt; LTV, set the CLTV to 'Not Available.'</p> <p>This disclosure is subject to the widely varying standards originators use to verify Borrowers' secondary mortgage loan amounts and will not be updated.</p>	
10	dti	<p><b>ORIGINAL DEBT-TO-INCOME (DTI) RATIO</b> - Disclosure of the debt to income ratio is based on (1) the sum of the borrower's monthly debt payments, including monthly housing expenses that incorporate the mortgage payment the borrower is making at the time of the delivery of the mortgage loan to Freddie Mac, divided by (2) the total monthly income used to underwrite the loan as of the date of the origination of the such loan.</p> <p>Ratios greater than 65% are indicated that data is Not Available. All loans in the HARP dataset will be disclosed as Not Available.</p> <p>This disclosure is subject to the widely varying standards originators use to verify Borrowers' assets and liabilities and will not be updated.</p>	<p>0% &lt; DTI ≤ 65%</p> <p>999 = Not Available</p> <p>HARP ranges:</p> <p>999 = Not Available</p>
11	orig_upb	<b>ORIGINAL UPB</b> - The UPB of the mortgage on the note date.	Amount will be rounded to the nearest \$1,000
12	ltv	<p><b>ORIGINAL LOAN-TO-VALUE (LTV)</b> - In the case of a purchase mortgage loan, the ratio obtained by dividing the original mortgage loan amount on the note date by the lesser of the mortgaged property's appraised value on the note date or its purchase price.</p> <p>In the case of a refinance mortgage loan, the ratio obtained by dividing the original mortgage loan amount on the note date and the mortgaged property's appraised value on the note date.</p> <p>In the case of a seasoned mortgage loan, if the Seller cannot warrant that the value of the mortgaged property has not declined since the note date, Freddie Mac requires that the Seller must provide a new appraisal value, which is used in the LTV calculation.</p> <p>Ratios below 6% or greater than 105% will be disclosed as "Not Available," indicated by 999. For loans in the HARP dataset, LTV ratios less than or equal to 80% and greater than 99% will be disclosed as Not Available.</p>	<p>6% - 105%</p> <p>999 = Not Available</p>
13	int_rt	<b>ORIGINAL INTEREST RATE</b> - The original note rate as indicated on the mortgage note.	
14	channel	<p><b>CHANNEL</b> - Disclosure indicates whether a Broker or Correspondent, as those terms are defined below, originated or was involved in the origination of the mortgage loan. If a Third-Party Origination is applicable, but the Seller does not specify Broker or Correspondent, the disclosure will indicate "TPO Not Specified". Similarly, if neither Third-Party Origination nor Retail designations are available, the disclosure will indicate "TPO Not Specified." If a Broker, Correspondent or Third-Party Origination disclosure is not applicable, the mortgage loan will be designated as Retail, as defined below.</p> <p>Broker is a person or entity that specializes in loan originations, receiving a commission (from a Correspondent or other lender) to match Borrowers and lenders. The Broker performs some or most of the loan processing functions, such as taking loan applications, or ordering credit reports, appraisals and title reports. Typically, the Broker does not underwrite or service the mortgage loan and generally does not use its own funds for closing; however, if the Broker funded a mortgage loan on a lender's behalf, such a mortgage loan is considered a "Broker" third party origination mortgage loan. The mortgage loan is generally closed in the name of the lender who commissioned the Broker's services.</p> <p>Correspondent is an entity that typically sells the Mortgages it originates to other lenders, which are not Affiliates of that entity, under a specific commitment or as part of an ongoing relationship. The Correspondent performs some, or all, of the loan processing functions, such as: taking the loan application; ordering credit reports, appraisals, and title reports; and verifying the Borrower's income and employment. The Correspondent may or may not have delegated underwriting and typically funds the mortgage loans at settlement. The mortgage loan is closed in the Correspondent's name and the Correspondent may or may not service the mortgage loan. The Correspondent may use a Broker to perform some of the processing functions or even to fund the loan on its behalf; under such circumstances, the mortgage loan is considered a "Broker" third party origination mortgage loan, rather than a "Correspondent" third party origination mortgage loan.</p> <p>Retail Mortgage is a mortgage loan that is originated, underwritten and funded by a lender or its Affiliates. The mortgage loan is closed in the name of the lender or its Affiliate and if it is</p>	<p>R = Retail</p> <p>B = Broker</p> <p>C = Correspondent</p> <p>T = TPO Not Specified</p> <p>9 = Not Available</p>

		sold to Freddie Mac, it is sold by the lender or its Affiliate that originated it. A mortgage loan that a Broker or Correspondent completely or partially originated, processed, underwrote, packaged, funded or closed is not considered a Retail mortgage loan. For purposes of the definitions of Correspondent and Retail, "Affiliate" means any entity that is related to another party as a consequence of the entity, directly or indirectly, controlling the other party, being controlled by the other party, or being under common control with the other party.	
15	ppmt_pnlty	<b>PREPAYMENT PENALTY MORTGAGE (PPM) FLAG</b> - Denotes whether the mortgage is a PPM. A PPM is a mortgage with respect to which the borrower is, or at any time has been, obligated to pay a penalty in the event of certain repayments of principal.	Y = PPM N = Not PPM
16	prod_type	<b>PRODUCT TYPE</b> - Denotes that the product is a fixed-rate mortgage.	FRM – Fixed Rate Mortgage
17	st	<b>PROPERTY STATE</b> - A two-letter abbreviation indicating the state or territory within which the property securing the mortgage is located.	AL, TX, VA, etc.
18	prop_type	<b>PROPERTY TYPE</b> - Denotes whether the property type secured by the mortgage is a condominium, leasehold, planned unit development (PUD), cooperative share, manufactured home, or Single-Family home. If the Property Type is Not Available, this will be indicated by 99.	CO = Condo PU=PUD MH = Manufactured Housing SF = 1-4 Fee Simple CP = Co-op 99 = Not Available
19	zipcode	<b>POSTAL CODE</b> – The postal code for the location of the mortgaged property	1. #####00, where "####" represents the first three digits of the 5-digit postal code Space(5)= Unknown
20	id_loan	<b>LOAN SEQUENCE NUMBER</b> - Unique identifier assigned to each loan.	F1YYQnXXXXXX F1 = product (Fixed Rate Mortgage); YYQn = origination year and quarter; and, XXXXXX = randomly assigned digits
21	loan_purpose	<b>LOAN PURPOSE</b> - Indicates whether the mortgage loan is a Cash- out Refinance mortgage, No Cash-out Refinance mortgage, or a Purchase mortgage. Generally, a Cash-out Refinance mortgage loan is a mortgage loan in which the use of the loan amount is not limited to specific purposes. A mortgage loan placed on a property previously owned free and clear by the Borrower is always considered a Cash-out Refinance mortgage loan. Generally, a No Cash-out Refinance mortgage loan is a mortgage loan in which the loan amount is limited to the following uses: Pay off the first mortgage, regardless of its age Pay off any junior liens secured by the mortgaged property, that were used in their entirety to acquire the subject property Pay related closing costs, financing costs and prepaid items, and Disburse cash out to the Borrower (or any other payee) not to exceed 2% of the new refinance mortgage loan or \$2,000, whichever is less. As an exception to the above, for construction conversion mortgage loans and renovation mortgage loans, the amount of the interim construction financing secured by the mortgaged property is considered an amount used to pay off the first mortgage. Paying off unsecured liens or construction costs paid by the Borrower outside of the secured interim construction financing is considered cash out to the Borrower, if greater than \$2000 or 2% of loan amount. This disclosure is subject to various special exceptions used by Sellers to determine whether a mortgage loan is a No Cash-out Refinance mortgage loan.	P = Purchase C = Cash-out Refinance N = No Cash-out Refinance 9 =Not Available
22	orig_loan_term	<b>ORIGINAL LOAN TERM</b> - A calculation of the number of scheduled monthly payments of the mortgage based on the First Payment Date and Maturity Date. Loans with original term of 420 or more, or 300 or less, are excluded from the Dataset if originated prior to 1/1/2005. If loan was originated on/after 1/1/2005, this exclusion does not apply.	Calculation: (Loan Maturity Date (MM/YY) – Loan First Payment Date (MM/YY) + 1)
23	cnt_borr	<b>NUMBER OF BORROWERS</b> - The number of Borrower(s) who are obligated to repay the mortgage note secured by the mortgaged property. Disclosure denotes only whether there is one borrower, or more than one borrower associated with the mortgage note. This disclosure will not be updated to reflect any subsequent assumption of the mortgage note.	.01 = 1 borrower .02 = > 1 borrowers .99 = Not Available
24	seller_name	<b>SELLER NAME</b> - The entity acting in its capacity as a seller of mortgages to Freddie Mac at	Name of the seller, or "Other

		the time of acquisition. Seller Name will be disclosed for sellers with a total Original UPB representing 1% or more of the total Original UPB of all loans in the Dataset for a given calendar quarter. Otherwise, the Seller Name will be set to "Other Sellers".	Sellers"
25	servicer_name	<b>SERVICER NAME</b> - The entity acting in its capacity as the servicer of mortgages to Freddie Mac as of the last period for which loan activity is reported in the Dataset. Servicer Name will be disclosed for servicers with a total Original UPB representing 1% or more of the total Original UPB of all loans in the Dataset for a given calendar quarter. Otherwise, the Servicer Name will be set to "Other Servicers".	Name of the servicer, or "Other Servicers"
26	flag_sc	<b>SUPER CONFORMING FLAG</b> – For mortgages that exceed conforming loan limits with origination dates on or after 10/1/2008 and settlements on or after 1/1/2009	1. Y = Yes . Space (1) = Not Super Conforming

Source: Freddie Mac.

#### 4.1.2. Performance Data

Table 9: Performance File, Data Dictionary

#	Origination Variable	Description	Allowable Values
1	id_loan	<b>LOAN SEQUENCE NUMBER</b> - Unique identifier assigned to each loan.	F1YYQnXXXXXX <ul style="list-style-type: none"> <li>F1 = product (Fixed Rate Mortgage);</li> <li>YYQn = origination year and quarter; and,</li> <li>XXXXXX = randomly assigned digits</li> </ul>
2	svcg_cycle	<b>MONTHLY REPORTING PERIOD</b> – The as-of month for loan information contained in the loan record.	YYYYMM
3	current_upb	<b>CURRENT ACTUAL UPB</b> - The Current Actual UPB reflects the mortgage ending balance as reported by the servicer for the corresponding monthly reporting period. For fixed rate mortgages, this UPB is derived from the mortgage balance as reported by the servicer and includes any scheduled and unscheduled principal reductions applied to the mortgage.  For mortgages with loan modifications, as indicated by "Y" in the Modification Flag field, the current actual unpaid principal balance may or may not include partial principal forbearance. If applicable, for loans with partial principal forbearance, the current actual unpaid principal balance equals the sum of interest bearing UPB (the amortizing principal balance of the mortgage) and the deferred UPB (the principal forbearance balance).  Current UPB will be rounded to the nearest \$1,000 for the first 6 months after origination date. This was previously reported as zero for the first 6 months after the origination date.	<b>Calculation:</b> (interest bearing UPB) + (non-interest bearing UPB)
4	delq_sts	<b>CURRENT LOAN DELINQUENCY STATUS</b> – A value corresponding to the number of days the borrower is delinquent, based on the due date of last paid installment ("DDLPT") reported by servicers to Freddie Mac, and is calculated under the Mortgage Bankers Association (MBA) method.  If a loan has been acquired by REO, then the Current Loan Delinquency Status will reflect the value corresponding to that status (instead of the value corresponding to the number of days the borrower is delinquent).	<ul style="list-style-type: none"> <li>XX = Unknown</li> <li>0 = Current, or less than 30 days past due</li> <li>1 = 30-59 days delinquent</li> <li>2=60–89days delinquent</li> <li>3=90–119days delinquent</li> <li>And so on...</li> <li>R = REO Acquisition</li> <li>Space (3) = Unavailable</li> </ul>
5	loan_age	<b>LOAN AGE</b> - The number of months since the note origination month of the mortgage.	<b>Calculation:</b> ((Monthly

		To ensure the age measurement commences with the first full month after the note origination month, subtract 1.	Reporting Period) – Loan Origination Date (MM/YY)) – 1 month
6	mths_remng	<b>REMAINING MONTHS TO LEGAL MATURITY</b> - The remaining number of months to the mortgage maturity date. For mortgages with loan modifications, as indicated by “Y” in the Modification Flag field, the calculation uses the modified maturity date.	<b>Calculation:</b> (Maturity Date (MM/YY) – Monthly Reporting Period (MM/YY))
7	repch_flag	<b>REPURCHASE FLAG</b> - Indicates loans that have been repurchased or made whole (not inclusive of pool-level repurchase settlements). This field is only populated only at loan termination month.	<ul style="list-style-type: none"> <li>N = Not Repurchased</li> <li>Y = Repurchased</li> <li>Space (1) = Not Applicable</li> </ul>
8	flag_mod	<b>MODIFICATION FLAG</b> – For mortgages with loan modifications, indicates that the loan has been modified.	<ul style="list-style-type: none"> <li>Y = Yes</li> <li>Space (1) = Not Modified</li> </ul>
9	cd_zero_bal	<b>ZERO BALANCE CODE</b> - A code indicating the reason the loan's balance was reduced to zero.	<ul style="list-style-type: none"> <li>01 = Prepaid or Matured (Voluntary Payoff)</li> <li>02 = Third Party Sale</li> <li>03=ShortSale or Charge Off</li> <li>06 = Repurchase prior to Property Disposition</li> <li>09 = REO Disposition</li> <li>15 = Note sale/Reperforming sale</li> </ul>
10	dt_zero_bal	<b>ZERO BALANCE EFFECTIVE DATE</b> - The date on which the event triggering the Zero Balance Code took place.	<ul style="list-style-type: none"> <li>YYYYMM</li> <li>Space(6) = Not Applicable</li> </ul>
11	current_int_rt	<b>CURRENT INTEREST RATE</b> - Reflects the current interest rate on the mortgage note, considering any loan modifications.	
12	non_int_brng_upb	<b>CURRENT DEFERRED UPB:</b> The current non-interest bearing UPB of the modified mortgage.	\$ Amount. Non-Interest Bearing UPB.
13	dt_lst_pi	<b>DUE DATE OF LAST PAID INSTALLMENT (DDLPI):</b> The due date that the loan’s scheduled principal and interest is paid through, regardless of when the installment payment was actually made.	<ul style="list-style-type: none"> <li>YYYYMM</li> </ul>
14	mi_recoveries	<b>MI RECOVERIES</b> - Mortgage Insurance Recoveries are proceeds received by Freddie Mac in the event of credit losses. These proceeds are based on claims under a mortgage insurance policy.	\$ Amount. MI Recoveries.
15	net_sale_proceeds	<b>NET SALES PROCEEDS</b> - The amount remitted to Freddie Mac resulting from a property disposition or loan sale (which in the case of bulk sales, may be an allocated amount) once allowable selling expenses have been deducted from the gross sales proceeds. A value of “C” in Net Sales Proceeds stands for Covered, which means that as part of the property disposition process, Freddie Mac was “Covered” for its total indebtedness (defined as UPB at disposition plus delinquent accrued interest) and net sale proceeds covered default expenses incurred by Servicer during the disposal of the loan. A value of “U” indicates that the amount is unknown.	\$ Amount. Gross Sale Proceeds – Allowable Selling Expenses. C = Covered U = Unknown
16	non_mi_recoveries	<b>NON-MI RECOVERIES:</b> Non-MI Recoveries are proceeds received by Freddie Mac based on repurchase/make whole proceeds, non-sale income such as refunds (tax or insurance), hazard insurance proceeds, rental receipts, positive escrow and/or other miscellaneous credits.	\$ Amount. Non-MI Recoveries.
17	expenses	<b>EXPENSES</b> - Expenses will include allowable expenses that Freddie Mac bears in the process of acquiring, maintaining and/ or disposing a property (excluding selling expenses, which are subtracted from gross sales proceeds to derive net sales proceeds). This is an aggregation of Legal Costs, Maintenance and Preservation Costs, Taxes and Insurance, and Miscellaneous Expenses	\$ Amount. Allowable Expenses.

18	legal_costs	<b>LEGAL COSTS</b> - The amount of legal costs associated with the sale of a property (but not included in Net Sale Proceeds). Prior to population of a Zero Balance Code equal to 03 or 09, this field will be populated as "Not Applicable," Following population of a Zero Balance Code equal to 03 or 09, this field will be updated (as applicable) to reflect the cumulative total. Space(12) – Not applicable	\$ Amount
19	maint_pres_costs	<b>MAINTENANCE AND PRESERVATION COSTS</b> –The amount of maintenance, preservation, and repair costs, including but not limited to property inspection, homeowner's association, utilities, and REO management, that is associated with the sale of a property (but not included in Net Sale Proceeds). Prior to population of a Zero Balance Code equal to 03 or 09, this field will be populated as "Not Applicable," Following population of a Zero Balance Code equal to 03 or 09, this field will be updated (as applicable) to reflect the cumulative total. Space (12) – Not applicable	\$ Amount
20	taxes_ins_costs	<b>TAXES AND INSURANCE</b> – The amount of taxes and insurance owed that are associated with the sale of a property (but not included in Net Sale Proceeds). Prior to population of a Zero Balance Code equal to 03 or 09, this field will be populated as "Not Applicable,". Following population of a Zero Balance Code equal to 03 or 09, this field will be updated (as applicable) to reflect the cumulative total. Space(12) – Not applicable	\$ Amount
21	misc_costs	<b>MISCELLANEOUS EXPENSES</b> - Miscellaneous expenses associated with the sales of the property but not included in Net Sale Proceeds). Prior to population of a Zero Balance Code equal to 03 or 09, this field will be populated as "Not Applicable,". Following population of a Zero Balance Code equal to 03 or 09, this field will be updated (as applicable) to reflect the cumulative total. Space(12) – Not applicable.	\$ Amount
22	actual_loss	<p><b>ACTUAL LOSS CALCULATION</b> - Actual Loss was calculated using the below approach:</p> <p><u>Actual Loss</u> = (Default UPB – Net Sale_Proceeds) + Delinquent Accrued Interest - Expenses – MI Recoveries – Non-MI Recoveries.</p> <p><u>Delinquent Accrued Interest</u> = (Default_Upb – Non-Interest bearing UPB) * (Current Interest rate – 0.35) * (Months between Last Principal &amp; Interest paid to date and zero balance date) * 30/360/100.</p> <p>Please note that the following business rules are applied to this calculation:</p> <ol style="list-style-type: none"> <li>For all loans, 35 bps is used as a proxy for servicing fee</li> <li>The Actual Loss Calculation will be set to zero for loans with Repurchase Flag = 'Y'</li> <li>The Actual Loss Calculation will be set to zero for loans with Net Sale Proceeds = C (Covered)</li> <li>The Actual Loss Calculation will be set to zero for loans with Net Sales Proceeds = 'U' (Net Sales Proceeds are missing, or expenses are not available.</li> <li>The Actual Loss Calculation will be set to missing for loans disposed within three months prior to the performance cutoff date.</li> <li>Modification Costs are currently not included in the calculation of the Actual Loss Calculation Field</li> </ol>	\$ Amount
23	modcost	<p><b>MODIFICATION COST</b> - The cumulative modification cost amount calculated when Freddie Mac determines such mortgage loan has experienced a rate modification event. Modification Cost</p> <p>is applicable for loans with rate changes only. This amount will be calculated on a monthly basis beginning with the first reporting period a modification event is reported and disclosed in the last performance record.</p> <p>For example:</p> <p>(Original Interest Rate/1200 * Current Actual UPB) – (Current Interest Rate/1200 * (sum (Current Actual UPB, -Current Deferred UPB)) and aggregate each month since modification through the Performance Cutoff Date into a cumulative amount</p>	\$ Amount
24	stepmod_ind	<b>STEP MODIFICATION FLAG</b> – A Y/N flag will be disclosed for every modified loan, to denote if the terms of modification agreement call for note rate to increase over time.	<ul style="list-style-type: none"> <li>Y = Yes</li> <li>N=No</li> <li>Space (1) = Not Step Mod</li> </ul>
25	dpm_ind	<b>DEFERRED PAYMENT MODIFICATION</b> – A Y/N flag will be disclosed to indicate Deferred Payment Modification for the loan.	<ul style="list-style-type: none"> <li>Y = Yes</li> <li>N=No</li> </ul>

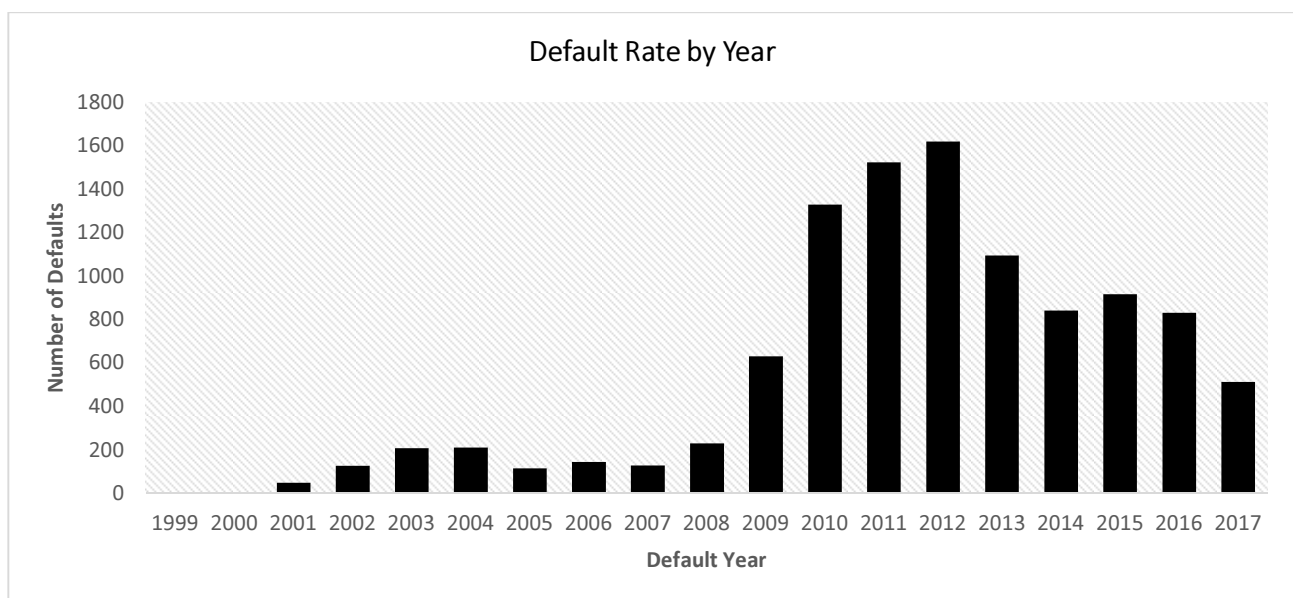
Source: Freddie Mac.

Many of these variables were eliminated throughout the cleaning process of the data. This is due to either the missing value ratios when compared to the count of observations, or the fact that the variable might not be valid in our studies. For instance, the postal code variable here was excluded from our final dataset as we are not concerned of the geographical location of the property. Other variables were all included in the study, however, we also used some feature engineering techniques to create two new features that will be discussed in section 4.3.2. The most important features are highlighted in section 4.3.1.

## 4.2. Exploratory Analysis

Many economists consider the 2008 financial crisis as one of the worse since the great depression of the 30s<sup>1</sup>. It began with a crisis in the subprime mortgage market in the United States and developed into a financial turmoil, and later to a full-blown international banking crisis. Several factors abetted to magnify the financial impact globally, but one main factor contributed the most, which the misperception and mismanagement of risk. Perhaps the precipitating factor was a high default rate in the United States subprime home mortgage sector.

*Graph 2: Default Rate by Year across our dataset*



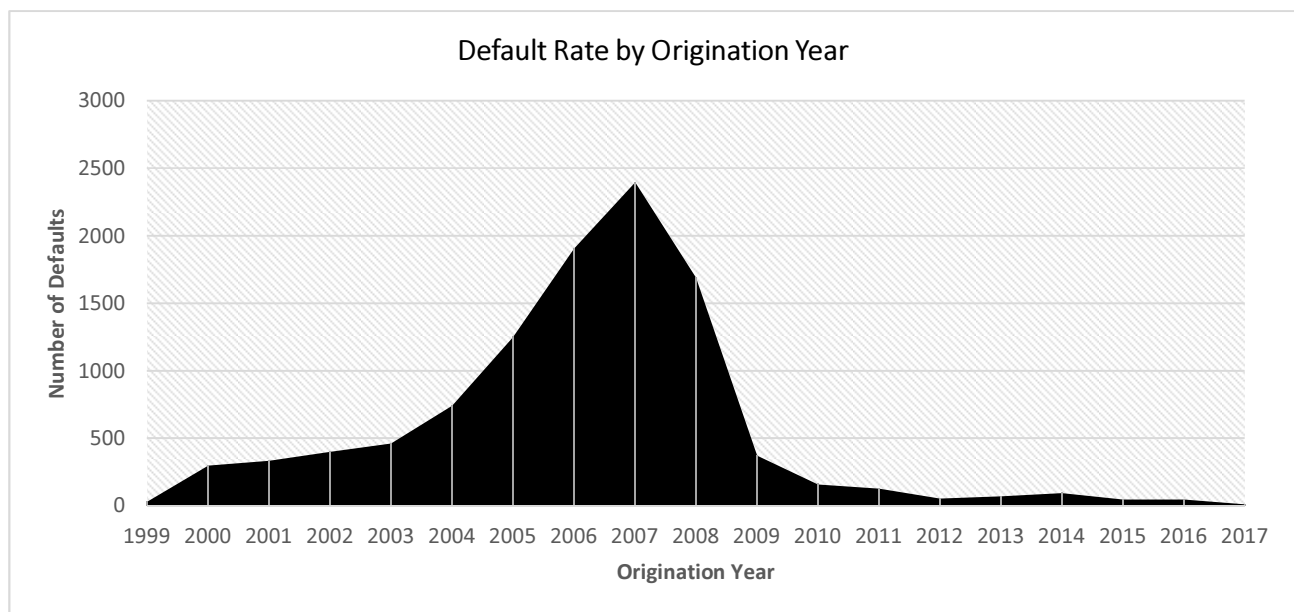
**Source:** Authors preparation.

<sup>1</sup> Referenced from a speech by Mr. Ben S Bernanke, Chairman of the Board of Governors of the US Federal Reserve System, at the conference co-sponsored by the Centre for Economic Policy Studies and the Bendheim Centre for Finance, Princeton, New Jersey, 24 September 2010.

Observing the default rate in our data, we will notice that the loans were quite stable during the period from 1999 to 2008/2009, however it abruptly ascended in the following years. This is demonstrated in Graph 2.

Loans originated within the years 2006 and 2008 mostly defaulted. Here is where the risk managers dropped the ball and the mortgage sector mainly lent money to all home-owner seekers with no collateral. Graph 3 demonstrates this claim.

*Graph 3: Default Rate by Origination Year*



**Source:** Authors preparation.

Although the Loan performance improved, as shown in Graph 3, however the impact of the inattentive mortgages initiated still exists. The improvement though is a result of the regulatory agencies improving their risk assessment and tauten their lending conditions.

#### **4.3. Data Wrangling**

As previously stated, the dataset provided as two sets of data, Loan-level origination files, and monthly loan performance. We now explore the imported data and get the dataset ready for the model to be applied. Freddie Mac made two sets of files publicly available, the first set of files deliver the loan data

at the moment of origination, and the set of files deliver the loan performance on monthly basis. File layouts and data dictionary were provided in section 4.1. and 4.2., representing loan-level origination files and loan-level performance files respectively.

- **Loan-level Origination Files**

We created a data frame where we append all the data from the sample files for the years 1999 to 2017. The appended file has 26 variables which holds various details associated with the loan origination annually. An important variable here is the Loan ID, which will be used later to link the loan performance appended file to the origination one. The Loan ID is unique in the origination file.

- **Loan-level Performance Files**

We created a data frame where we append all the data from the sample files for the years 1999 to 2017. The appended file has 23 variables which holds various details associated with the borrower status quo on monthly basis. In this file, the Loan ID is not unique as it contains the loan performance on monthly basis, so within one year the Loan ID might be repeated twelve times (if the loan did not default). Therefore, our next step is to ensure the Loan ID variable is distinguished. That said, we selected only the Loan ID with the highest Loan age value, as this would represent the final outcome of the selected loan, whether it was defaulted or not.

#### **4.3.1. Feature Importance**

Subsequently, we join the two sets of data, Origination and Performance ones by our Unique variable, the Loan ID, but before we proceed any further, it is imperative to select which attributes in our data that are most relevant to the predictive model that we are building. (Guyon & Elisseeff, 2003) highlighted that the objective of variable selection is threefold: improving the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data.



Propitiously, *Caret R Package* can automatically rank all variables available by its importance by building a model. This package can also remove any redundant variables by building a correlation matrix of the data's attributes and reports on attributes that are highly correlated with each other, which can be removed. For simplicity, we will be ranking our variables by importance in our project. One of the most widely used model that presents the importance of a variable in a dataset is Random Forest (RF). Constructing this model, we discover that the "Zero Balance Code", and the "Current Loan Delinquency Status" are ranked the highest. Both variables play an instrumental role in determining whether a loan defaulted or not. "Loan Age", "Credit Score", and "Original Combined Loan-to-Value" were also in the list.

#### **4.3.2. Feature Engineering**

Before engineering a new feature (or variable), we studied the variables that would reflect to us which loan has defaulted and which has not. Based on the definition provided by Freddie Mac, each loan should be in one of three stages: Prepaid (loans that were fully paid before or after the expiration of the mortgage), Paying (loans that are still active), and Default (loans that were not fully paid).

- **Default Status Variable**

We calculated default using current loan delinquency status given in the data. Delinquency status measures the number of days the borrower is delinquent (i.e. couldn't meet up with monthly obligations) as specified by Freddie Mac. In the data, status 0 implies current or less than 30 days, status 1 implies greater than 30 days but less than 60 days, status 2 implies greater than 60 days but less than 90 days while status 3 refers to delinquency for days between 90 and 119. We calculated maximum delinquency status for each loan and then specify the output variable as follows: if the maximum delinquency status is greater than 3 (i.e. loan is of delinquency status 3 and above) or zero balance code is greater than 9 (zero balance code is used to indicate why the loan balance was reduced to zero, 09 indicates deed in lieu loans) we classify such loan as default. If the zero-balance code is 01 (01 indicates prepaid or matured loans) we classify such loans as prepaid, the rest of the loans we classify as paying. New feature (Default Status) is engineered to represent the final outcome of each loan.

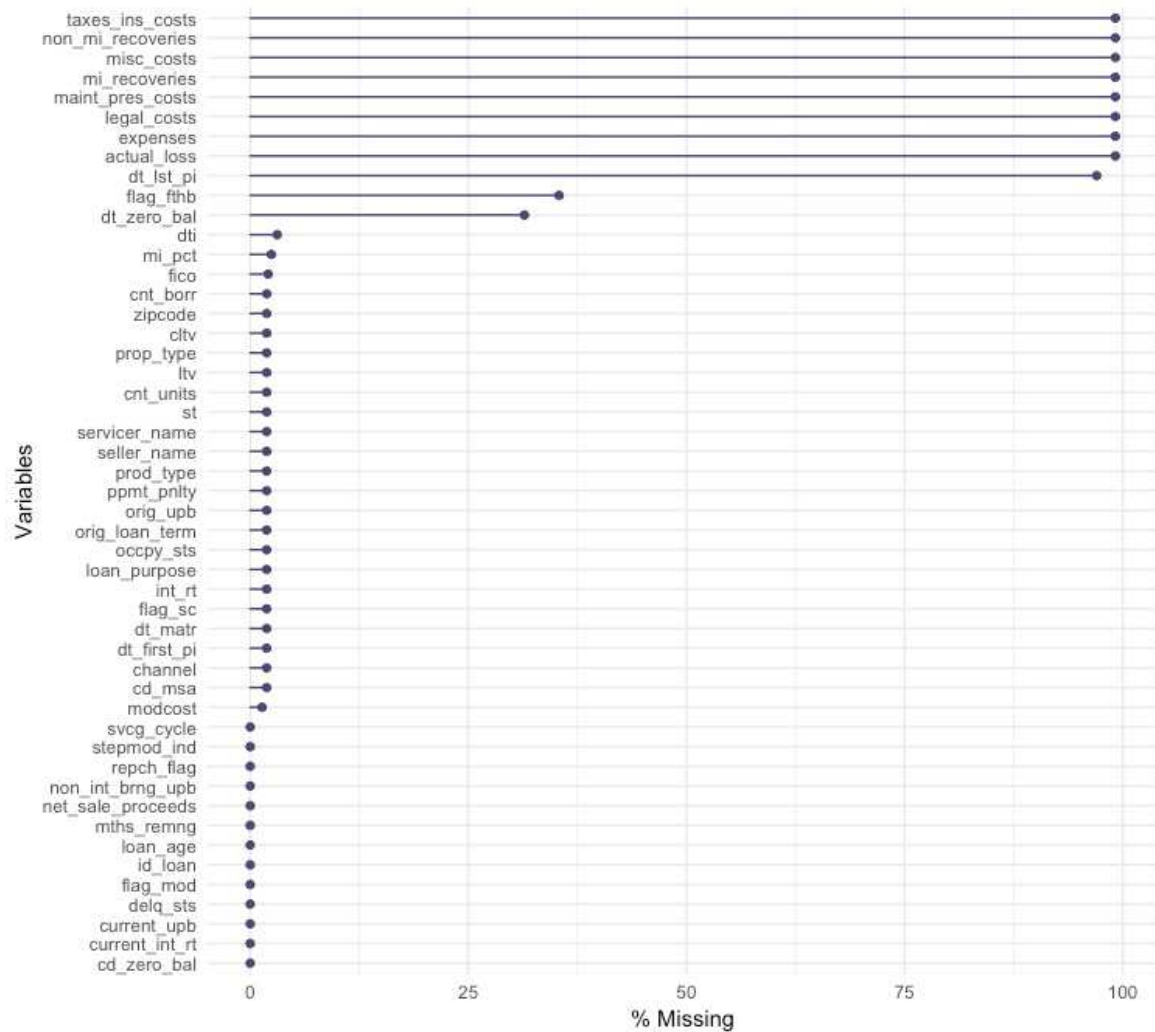
- **Credit Scoring Variable**

This newly created variable reflects another aspect of the borrower, which defines whether this borrower is “good” or “bad”. This is merely based on the FICO score provided in the data set. Any Borrower with 550 credit score or above is considered as a “good” borrower, lower than 550 is considered as a “bad” borrower.

#### **4.3.3. Missing Observations**

To visually explore the missing values, we plot the number of missing values for each variable. Graph 04 represents the variables on the ‘y’ axis and the volume of the missing items on the ‘x’ axis. We have almost 10 Variables with 100% of its observations are not available. Whether these variables were missing at random or not, we will exclude them from our studies as it will not be possible to be imputed. Graph 05 is the new representation of missing values versus variables after eliminating the variables with no observations. All the remaining missing values were imputed using mice. Mice merely builds a separate model for each missing observation and imputes it using all the observations in the given variables.

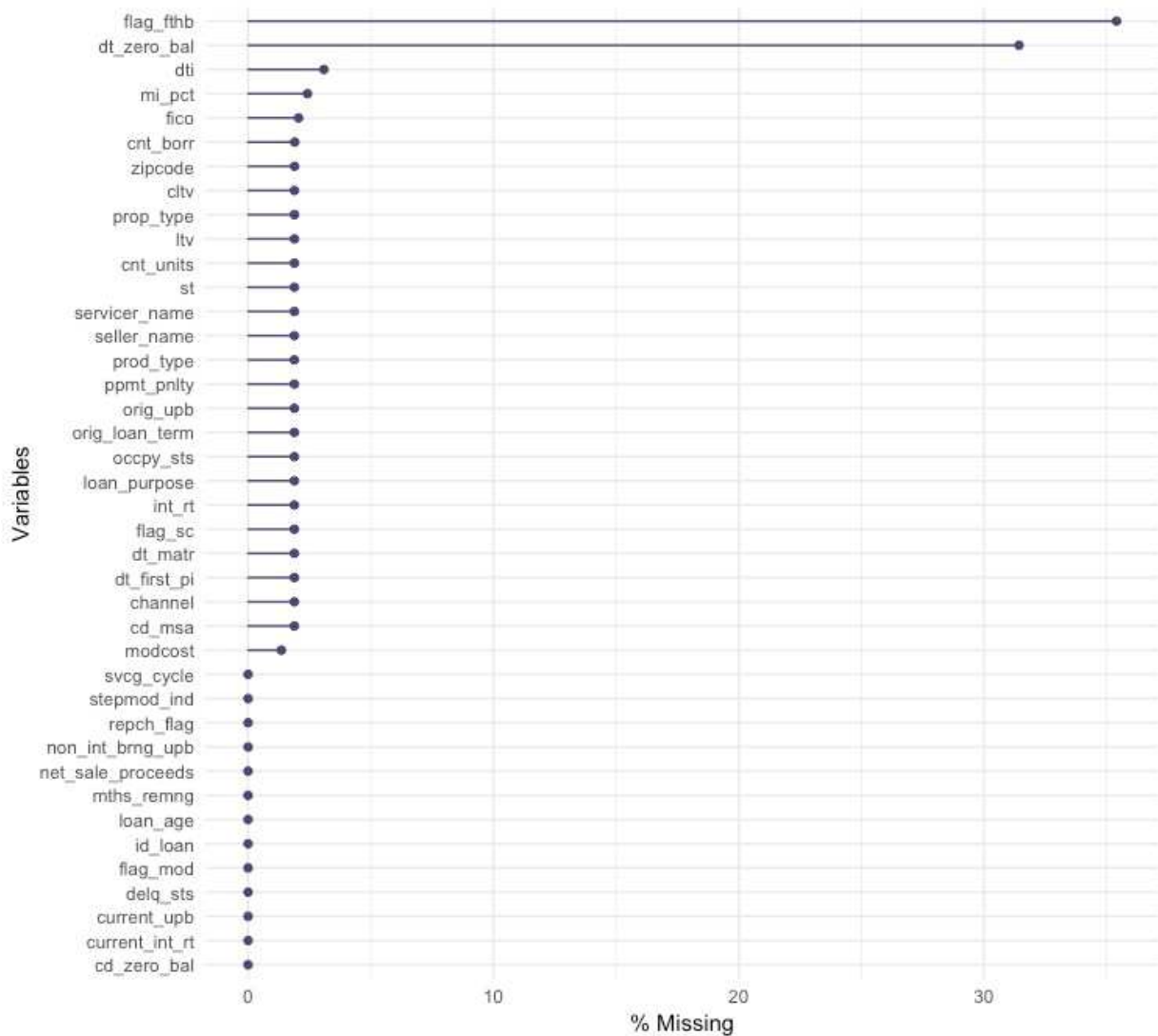
Graph 4: Missing Values Visualization



Source: Authors preparation.

While constructing the benchmark model, we will be working with two datasets, one with which all the missing observations has been omitted, and another dataset where all missing observations has been imputed using mice. We decided to test our modelling on both datasets to observe the prediction accuracy using both pre-processing techniques (Omitting NAs and Imputing NAs). The dataset that has a higher accuracy while building the Benchmark Model will be the one that we will proceed with to construct our predictive model using Ensemble Technique.

Graph 5: Missing Values Visualization after zero-variables elimination



Source: Authors preparation.

#### 4.4. Data Imbalance

One issue with the Freddie Mac loan level dataset is highly unbalanced distribution of the two classes default and non-default. 97% of the observations were defined as non-default while just 3% of the data is assigned to class 1 (defaulted). In this case the classifiers won't be able to recognize minor classes and are influenced by major classes. For example, in a logistic regression the conditional probability of

minor classes are underestimated (Cieslak & Chawla, 2008) and Tree based classifiers, and KNN yield high recall but low sensitivity when the data set is extremely unbalanced (King & Zeng, 2001).

Before fitting the model over the training dataset and forecast classes over the testing dataset, we should balance the data. There are different methods to balance the data such as oversampling , under-sampling, and Synthetic Minority Oversampling Technique (SMOTE) proposed by (Chawla, Bowyer, Hall & Kegelmeyer, 2002). Oversampling methods replicate the observations from the minority class to balance the data. However, adding the same observation to the original data causes overfitting, where the training accuracy is high but forecast accuracy over testing data is low. Conversely, the under-sampling methods remove the majority of classes to balance data. Obviously, removing observations causes the training data to lose useful information pertaining to the majority class. SMOTE finds random points within nearest neighbors of each minor observation and by boosting methods generates new minor observations. Since the new data are not the same as the existing data, the overfitting problem won't be an issue anymore, and we won't lose the information as much as with the under-sampling methods. For these reasons, this study considers the SMOTE function to balance the data.

## 5. Modelling

This part of the project aims to construct a predictive model using ensemble technique to guide the decision of accepting or refusing the sale of a mortgage loan to a prospective home owner, estimating his probability of default. The Splitting process of the data into “train” and “test” must be executed carefully to ensure that the same ratio of classes is present in the training set and the test set. For this to be accomplished, we use stratified sampling. Our data is split into two training datasets (35% each), and testing dataset of 30%. The purpose of the two training datasets will be explained in section 5.2.

### 5.1. Benchmark Model

In the simple logistic regression model, the output variable has two classes (e.g. 0 or 1). In our application, value 1 represents the loan status being default and 0 is the loan status equaling paying. The model was constructed using the ‘glm’ function in R. In our project, we are embracing a situation where we want to estimate if we will get a case of default in each particular customer that asks for a loan ( $Y \in \{0,1\}$ ), where 1 = Default and 0 = Non-default, so this should be modeled using a binomial distribution and logit link function. For any particular loan, we will have a vector of variables which may allow us to model default called predictor variables. We use  $X = (X_1, X_2, \dots, X_m)^T$  to represent a vector of random variables, as so, this is a classification problem, where we require the probability of the event, rather than just a point estimate of outcome.

Therefore, we are looking to develop a model to estimate  $P(Y = 1|X = x)$ , that represents the probability of default (PD), depending on characteristics  $x$ . The logistic regression model is then

$P(Y = 1|X = x) = f_L(\beta_o + \beta^T x)$  where  $f_L$  is the logistic link function (logit),  $f_L = \frac{1}{1+e^{-s}} = \frac{e^s}{1+e^s}$  and  $\beta_o$  is an intercept and  $\beta = (\beta_1, \dots, \beta_m)^T$  is a vector of coefficients, on for each predictor variable. Parameter estimates for  $\beta_o$  and  $\beta$  are obtained through MLE (Maximum Likelihood Methods).

Using  $z = f_L^{-1}(p) = \ln\left(\frac{p}{1-p}\right) \Rightarrow \text{logit}(p) = \ln\left(\frac{p}{1-p}\right)$ , with a logistic regression model, we represent the linear combination of explanatory variables as the logit of the success probability. The function  $s(x) = \beta_o + \beta^T x$  is then called the log-odds score since  $s(x) = f_L^{-1}[P(Y = 1|X = x)] = \log\left(\frac{P(Y=1|X=x)}{P(Y=0|X=x)}\right)$ .

The log-odds score is typically the basis of the credit score used by banks and credit bureaus to rank people. Implementing the prior criteria to both available datasets, with NAs Omitted and NAs Imputed, the resulted accuracy was as follows:

*Table 10: Accuracy Rate for Logistic Regression*

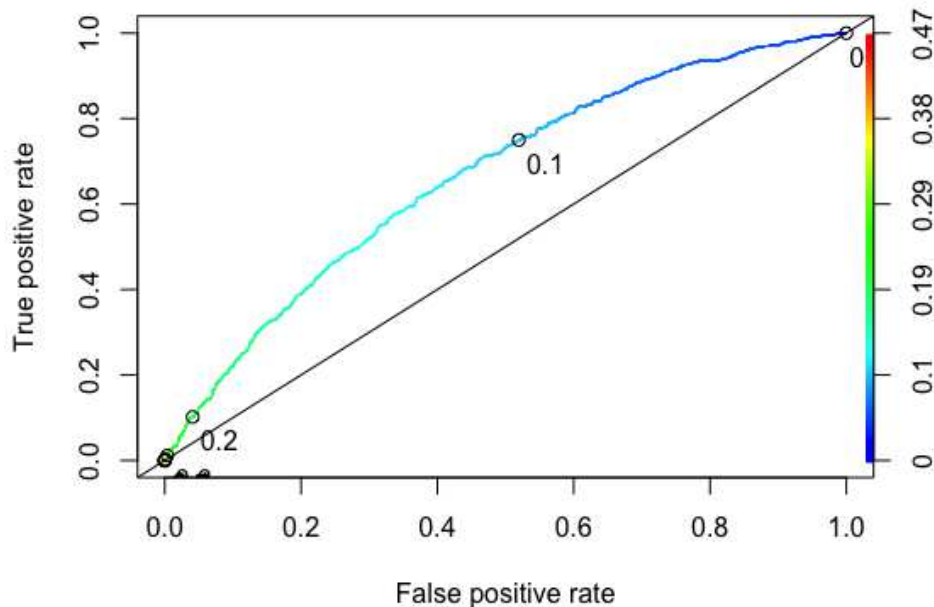
NAs Omitted	NAs Imputed
0.890376	0.8886399

**Source:** Authors preparation.

It is worthy to note that the benchmark model was applied to 70% of the data, which corresponds to the two 35% training datasets.

Graphs 6 and 7 are graphical representations of the trade-off between the percentage of true positives and false positives for every possible cut-off. This is known as the Receiver Operating Characteristic (ROC) curve. The accuracy of the model is measured by the area under the ROC curve. The closer the AUC value is to 1 the more statistically accurate the model is.

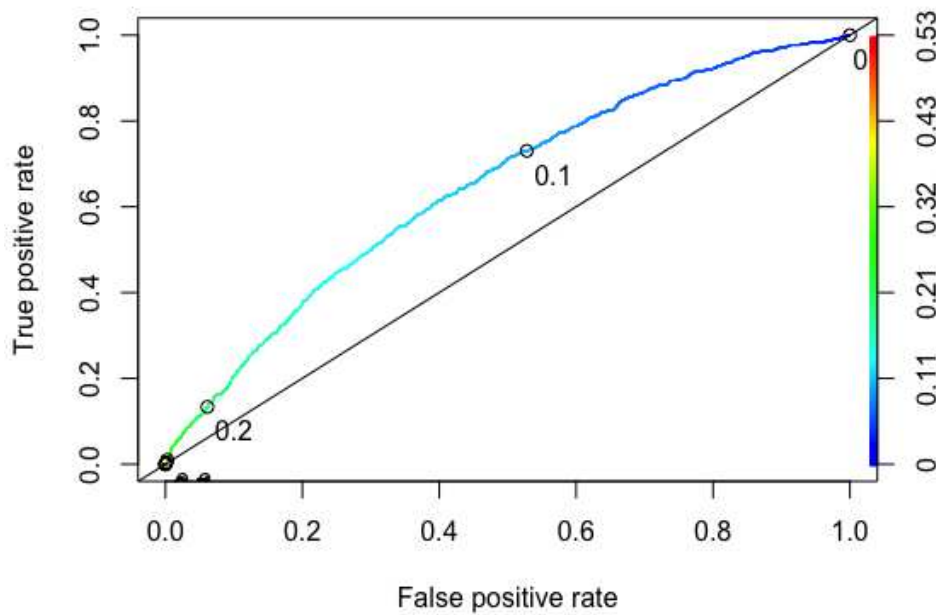
*Graph 6: ROC Curve based on the Eliminated NAs Model*



**Source:** Authors preparation.

The simple logistic regression has shown high level of accuracy with  $ACC = 0.890376$  for the NA Omitted Model, and  $ACC = 0.8886399$  for the NA Imputed Model, as shown in table 10.

*Graph 7: ROC Curve based on the Imputed NAs Model*



**Source:** Authors preparation.

Moving ahead this point, we will be working on building our predictive model using Ensemble technique only on the dataset with the NAs eliminated as the benchmark model had a higher prediction rate for the NAs eliminated dataset than the NAs imputed dataset.

## 5.2. Ensemble Technique

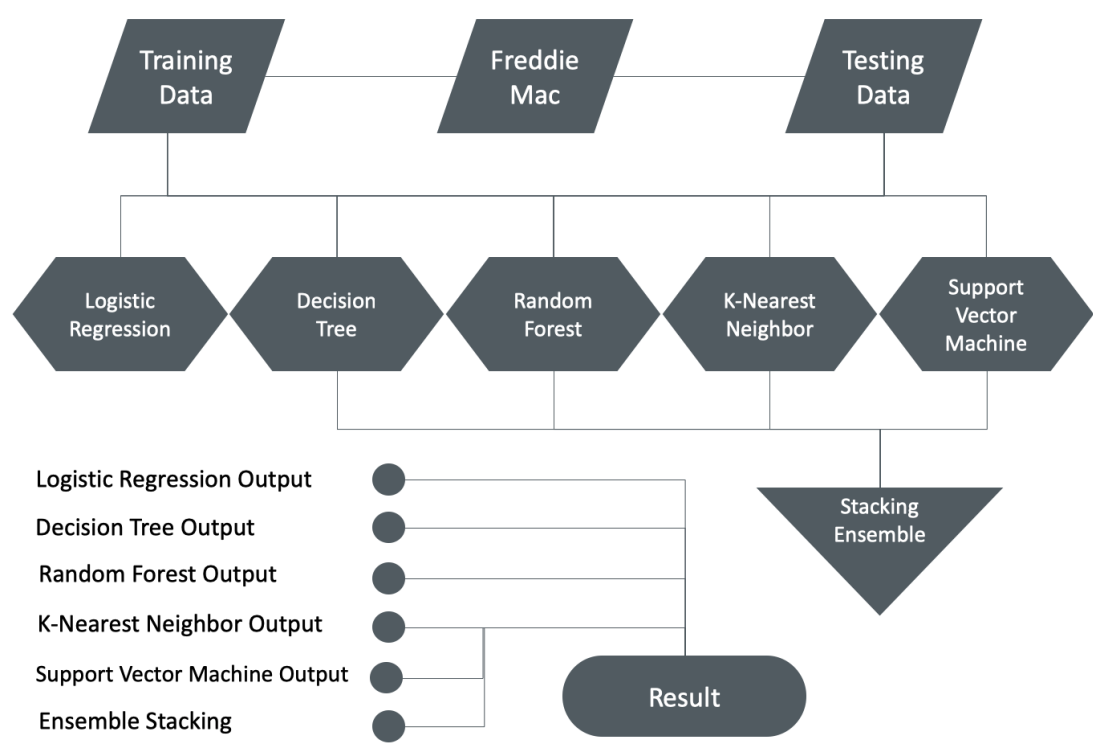
Ensembling is the process of combining predictions from multiple models to a single prediction for the purpose of improving classification performance. We combine predictions from two or more models trained on the same dataset to determine if they outperform the highest scoring single model. Each method is evaluated using stacking ensemble. Figure 10 illustrates the Ensemble scheme.

Applying the stacking ensemble technique to our data is to be done in two stages: The first stage is to fit the *first-level learners* to train the first training portion of the data, let's call it *train\_data1* (35% of the entire data), and create predictions for the second portion of the data, let's call it *train\_data2* (35% of the



entire data). We then fit the same models to train *train\_data2* and create predictions for *train\_data1*. We finally fit the models on the entire training data (70%) and create predictions for the test set (30% of the entire data). The second stage is to train the *meta-learner* on the probabilities of the *first-level learners*.

Figure 10: Ensemble Methodology



Source: Authors preparation.

When applying *decision tree* model on our data, more than 5000 trees were created due to the high number of categorical features present. As a matter of fact, one of the major benefits of this kind of method is its simplicity to understand and interpret. However, they are highly biased in favor to categorical variables. This model resulted on the least prediction rate with an accuracy of 0.8840072. On the other hand, *Random Forest* is constructed of a multitude of decision trees and outputting the class that is the mode of the classes (classification) of the individual trees. We used the R package “randomForest” to apply the model on our dataset. This model performance has a substantial increase of performance comparing to the previous models, with an accuracy of 0.8904202. Meanwhile, in applying *K-Nearest Neighbor* to our dataset, 200 different KNN model were created with different ‘K’ values

varying from 1 to 100 and accuracy of each model was tested by making prediction on the test data. We used “knn” function in R for this approach which returned to us the value of ‘K’ = 20 with overall accuracy of 0.8884684.

*Table 11: Accuracy Rate for Level One Classifiers*

Model	Accuracy
Decision Tree	0.8840072
Random Forest	0.8904202
K-Nearest Neighbor	0.8884684
Support Vector Machine	0.8904382

**Source:** Authors preparation.

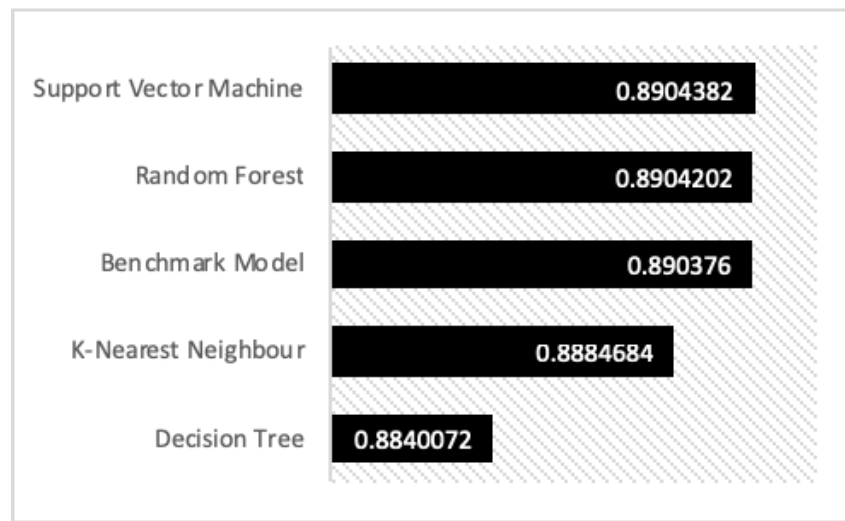
Applying support vector machine model to our dataset, was a little trickier since this model requires the dataset to be transformed to a format of SVM package, and conduct simple scaling to the data (Chih-Wei Hsu, Chih-Chung Chang, Hsu, Chang, & Lin, 2003). Our first step is to represent each observation in our dataset as a vector of real numbers, i.e. convert the categorical attributes into numeric data. For instance, the feature “Occupancy Status” has three attributes {P, I, S}, which was highlighted in the data dictionary section as P = Primary Residence, I = Investment Property and S = Second Home. Three features will be created and now presented as (0,0,1), (0,1,0), and (1,0,0). Our second step is to scale the data before applying the model. Scaling is mainly beneficial to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges. (Chih-Wei Hsu, Chih-Chung Chang et al., 2003) recommend linear scaling each attribute to the range  $[-1, +1]$  or  $[0, 1]$  for both training and testing data. The highest prediction rate for single classifiers was achieved upon applying this model to our data, with an accuracy of 0.8904382.

We now combine the outputs of each model to compute the ultimate prediction rate. After successfully combining these outputs, the prediction rate was boosted with an accuracy rate of 0.892572045.

## 6. Results

In this section, we will be presenting the results of our classification models. Graph 8 displays each model's accuracy and a comparison between them. Support Vector Machine had the highest prediction rate, with an accuracy of 0.8904382, and Random Forest had the second place with an accuracy of 0.8904202, followed by the benchmark model 0.890376. K-Nearest neighbor and decision trees had the least prediction rate with an accuracy of 0.8884684 and 0.8840072 respectively, as illustrated in table 11.

*Graph 8: Models' Accuracy*



**Source:** Authors preparation.

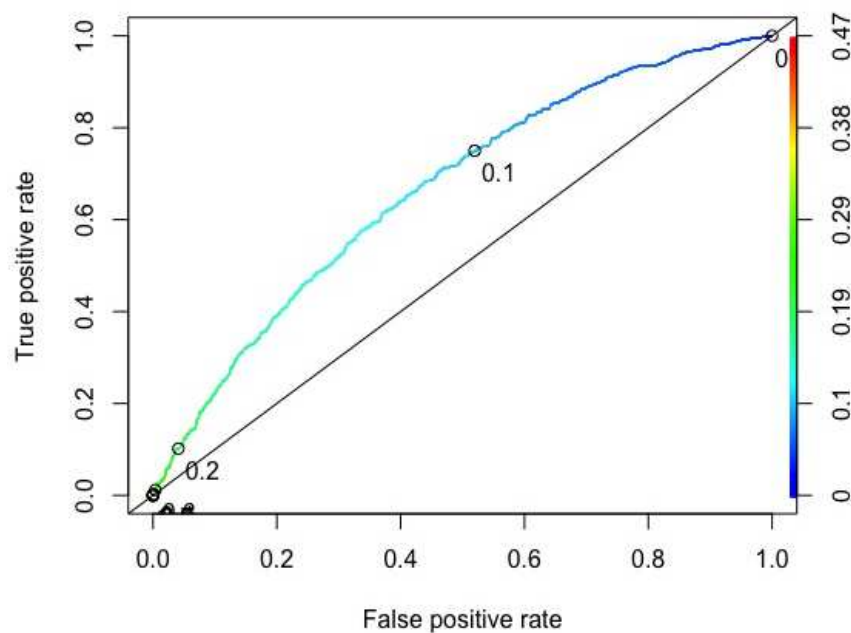
SVM delivered the highest accuracy rate amongst all first-level learners. This is expected given that SVM used kernel transformation to linearize the data as explained in section 5.2. Although the dataset used to fit the SVM model is much larger that can't be understood by looking at a spreadsheet, but in expanding the dataset there are now more obvious boundaries between our classes and the SVM algorithm is able to compute a much more optimal hyper-plane, which produces an accurate and robust classification results (Auria & Moro, 2009). Although in our studies we considered our benchmark model to be Logistic Regression model, yet, the Random Forest model outperformed it as (Lessmann et al., 2015) previously suggested, with a higher accuracy. It is imperative to mention that the approach used in the data preprocessing plays a vital role in the final outcome.

To determine enhancement of prediction through ensembling, every unique combination of selected algorithms is processed through building the meta-learner classifier, which acts as the Level two

classifier in our Ensembling Technique. The accuracy of combining the aforementioned outputs into a new classifier is 0.892572045. Graph 10 displays the accuracy measures for the models fit on the dataset in this study. The meta-learner outperforms all single predictors with an accuracy of 0.892572045. This is expected as the meta-learner is merely a combination of the outcome probabilities from first-level learners, i.e. it combined and enhanced these probabilities. SVM has an accuracy of 0.8904382, the highest after the meta-learner. Logistic regression and random forest models are almost similar to each other, higher than that of K-Nearest Neighbor.

Graph 9 presents the ROC curve for the meta-learner classifier. In a ROC curve, the horizontal axes are the true positive rate and the vertical axes is the false positive rate for different threshold points of parameters. Thus, if the curve is closer to the top left then the accuracy of the forecast is higher.

*Graph 9: ROC Curve of Ensemble Model*

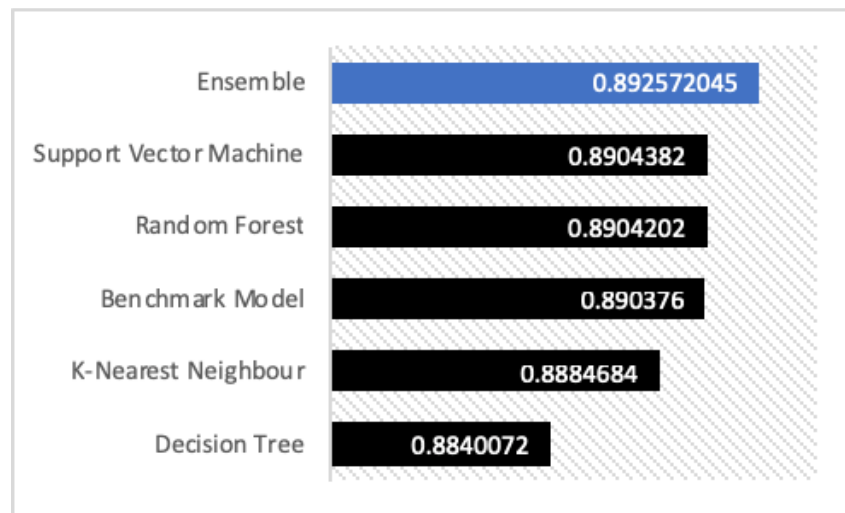


**Source:** Authors preparation.

Another important result of this study is to determine the important features that influence the risk of default, which sanctioned us to discover that the “Zero Balance Code” and the “Current Loan Delinquency Status” are ranked the highest by applying the Random Forest model on our dataset. Both

variables play an instrumental role in determining whether a loan defaulted or not. Generally, “Zero Balance Code”, “Current Loan Delinquency Status”, “Loan Age”, “Credit Score”, and “Original Combined Loan-to-Value” are the top five important features to predict loan default.

*Graph 10: Accuracy Comparison of Stacking Ensemble*



**Source:** Authors preparation.

The prediction accuracy has been enhanced using stacking ensembling with an 89.257%, outperforming that of traditional single classifiers.

## 7. Conclusion

For decades, banking institutions' main focus is to lend debtors' money, while these lenders mostly aim to purchase their dream house with the borrowed money. Banks' decision on whether to approve or reject a mortgage application is mostly based on the lenders' credit score. Credit score is a numerical expression that represents the borrower's creditworthiness, which is based on tremendous information being gathered by financial institutions both on the borrower and the underlying property of the mortgage. Statistical Modelling played an instrumental role in determining whether a prospective home owner would default or not. A benchmark model is the logistic regression, due to its interpretability. Since the revolution of big data, default's prediction became more and more intriguing area to be explored, and more sophisticated models were implemented that outperformed the traditional classifier model logistic regression. This paper is devoted to further enhance the logistic regression model by implementing a stacking ensemble technique, which is merely combining the outputs of different sophisticated models, (including Random Forest, K-Nearest Neighbor, Decision Tree, and Support Vector Machine) and use their probability outcome as an input for the Logistic Regression. Dataset used in our classification modelling is made publicly available by Freddie Mac.

This paper has been both data-focused and method-focused. Data-focused in the sense that the prediction models were based solely on mortgage dataset provided by Freddie Mac. Method-focused in the sense of basically applying stacking ensemble technique to classify mortgages into defaults and non-defaults loans. Given the data dictionary provided by Freddie Mac, and some data exploratory analysis techniques, we delve into the structure of both the loan origination and performance datasets as well as examine the relationship between default rate and certain variables. We implemented some data pre-processing techniques such as examining the relationship between the default rates and the dataset variables and construction of a random forest model to determine the variable importance. "Zero Balance Code", and the "Current Loan Delinquency Status" have the highest influential role in determining whether a loan defaulted or not. We then used feature engineering techniques to create a new classification variable that displays "1" for default loans, and "0" for non-default loans. We benchmarked our study by applying a logistic regression model to our dataset that yielded in a prediction accuracy of 88.86% for the dataset with missing observation imputed using mice, versus 89.04% for the dataset with missing observation omitted. The results confirm that applying machine learning methods

yields better forecast accuracy than traditional single classifier models such as logistic regression. The prediction accuracy of our stacking ensemble is 89.257% outperforming other models used in our study.

Despite the high accuracy of the meta-learner when compared to that of the first-learners, it is highly unlikely that this technique would be adopted to replace the commonly used Logistic Regression or Random Forest in Credit Score Analysis. The foremost reason is that the effort exerted to develop the model is disproportionate to the return. Although other techniques presented in this paper have a slightly lower classification power, yet, the ease of deployment would definitely play an instrumental role. In addition, these models are provided as built-in functions in some libraries that can be used quite effortlessly in R and Python, or in a drag-and-drop application such as Knime, or SAS Enterprise Miner. A model that is only slightly better most likely will not lead to a change in paradigm.

The technique presented in this paper is generic, solely based on the variables in the dataset. To produce a more robust model, it is necessary to engineer some new features including **Economical Features** such as “*unemployment rate*”, “*rent ratio*”, and “*vacant ratio*”. **Social Features** that would strengthen the model prediction would be “*divorce rates*”, and “*marriage rates*”. **Financial Feature** that could be included are “*Consumer Debt Percentage Change*”, and “*Mortgage Debt Percentage Change*”. These features might be relevant factors in mortgage defaults prediction. One could therefore further expand the study to include *Survival Analysis*. Survival Analysis is a statistical approach to estimate the expected time for an event to take place, in our case, when the “default” occurs. Another interesting model to explore is the *Cox Proportional Hazard* model, which is a method for estimating and analyzing the impact of several given features until an event happens. Both of these afore mentioned further research opportunities would allow us to examine the probability of survival and impact of different variables on the hazard rate. The timing when customers default is an interesting area to investigate since it can provide the bank with the ability to compute the probability over a customer’s lifetime and perform profit scoring.

## 8. References

- Addo, P. M., Guegan, D. & Hassani, B. (2018). *Credit Risk Analysis Using Machine and Deep Learning Models*. SSRN. <https://doi.org/10.2139/ssrn.3155047>
- Altman, N. S. (1992). An introduction to kernel and nearest-neighbor nonparametric regression. *American Statistician*. <https://doi.org/10.1080/00031305.1992.10475879>
- Auria, L. & Moro, R. A. (2009). *Support Vector Machines (SVM) as a Technique for Solvency Analysis*. SSRN. <https://doi.org/10.2139/ssrn.1424949>
- Azam, R., Danish, M. & Akbar, S. S. (2012). *The significance of socioeconomic factors on personal loan decision a study of consumer banking local private banks in Pakistan*. IQRA University.
- Bagherpour, A. (2017). *Predicting Mortgage Loan Default with Machine Learning Methods*.
- Banasik, J., Crook, J. N. & Thomas, L. C. (1999). Not if but when will borrowers default. *Journal of the Operational Research Society*, 50(12), 1185–1190. <https://doi.org/10.1057/palgrave.jors.2600851>
- Bash, E. (2015). *Machine Learning with R and H2O*. Packt. <https://doi.org/10.1017/CBO9781107415324.004>
- Bellotti, T. & Crook, J. (2009). Support vector machines for credit scoring and discovery of significant features. *Expert Systems with Applications*, 36(2 PART 2), 3302–3308. <https://doi.org/10.1016/j.eswa.2008.01.005>
- Bolarinwa, A. (2017). *Machine learning applications in mortgage default prediction*. University of Tampere. Retrieved from <http://urn.fi/URN:NBN:fi:uta-201712122923>
- Breiman, L. (1996). Bagging predictors. *Machine Learning*, 24(2), 123–140. <https://doi.org/10.1007/BF00058655>
- Breiman, L. (2001). Random forests. *Machine Learning*. <https://doi.org/10.1023/A:1010933404324>
- Breiman, L., Friedman, J. H., Olshen, R. A. & Stone, C. J. (1984). Classification and Regression Trees. The Wadsworth statisticsprobability series (Vol. 19). <https://doi.org/10.1371/journal.pone.0015807>
- Brown, D. R. (2012). *A Comparative Analysis of Machine Learning Techniques For Foreclosure Prediction*. Nova Southeastern University. Retrieved from [https://nsuworks.nova.edu/gscis\\_etd/105/](https://nsuworks.nova.edu/gscis_etd/105/)
- Brown, I. & Mues, C. (2012). An experimental comparison of classification algorithms for imbalanced credit scoring data sets. *Expert Systems with Applications*, 39(3), 3446–3453. <https://doi.org/10.1016/j.eswa.2011.09.033>
- Bühlmann, P. (2012). Bagging, boosting and ensemble methods. In *Handbook of Computational Statistics: Concepts and Methods: Second Edition*. [https://doi.org/10.1007/978-3-642-21551-3\\_\\_33](https://doi.org/10.1007/978-3-642-21551-3__33)



- Butaru, F., Chen, Q., Clark, B., Das, S., Lo, A. W. & Siddique, A. (2016). Risk and risk management in the credit card industry. *Journal of Banking & Finance*.  
<https://doi.org/10.1016/j.jbankfin.2016.07.015>
- Buuren, S. van & Groothuis-Oudshoorn, K. (2011). mice : Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*. <https://doi.org/10.18637/jss.v045.i03>
- Chamboko, R., Bravo, J. M. (2016). On the Modelling of Prognosis from Delinquency to Normal Performance on Retail Consumer Loans. *Risk Management* 18 (4), 264–287.
- Chamboko, R., Bravo, J. M. (2018a). Modelling and forecasting recurrent recovery events on consumer loans. *International Journal of Applied Decision Sciences*, Vol. 12, No. 3, 271-287.
- Chamboko, R., Bravo, J. M. (2018b). Frailty correlated default on retail consumer loans in developing markets. *International Journal of Applied Decision Sciences*, Vol. 12, No. 3, pp.257–270.
- Chamboko, R. & Bravo, J. M. (2018c). A multi-state approach to modelling intermediate events and multiple mortgage loan outcomes. Working Paper, submitted to *Journal of Banking and Finance*.
- Chawla, N. V., Bowyer, K. W., Hall, L. O. & Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*.  
<https://doi.org/10.1613/jair.953>
- Chih-Wei Hsu, Chih-Chung Chang, and C.-J. L., Hsu, C.-W., Chang, C.-C. & Lin, C.-J. (2003). A practical guide to support vector classification. *BJU International*.  
<https://doi.org/10.1177/02632760022050997>
- Cieslak, D. A. & Chawla, N. V. (2008). Learning decision trees for unbalanced data. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. [https://doi.org/10.1007/978-3-540-87479-9\\_34](https://doi.org/10.1007/978-3-540-87479-9_34)
- Cortes, C. & Vapnik, V. (1995). Support-Vector Networks. *Machine Learning*.  
<https://doi.org/10.1023/A:1022627411411>
- Cox, D. R. (1958). The Regression Analysis of Binary Sequences. *Journal of the Royal Statistical Society. Series B (Methodological)*. <https://doi.org/10.1007/BF03180993>
- Debajyoti Ghosh Roy, Bindya Kohli, S. K. (2013). BASEL I TO BASEL II TO BASEL III. *AIMA Journal of Management & Research*.
- Deng, G. (2016). *Analyzing the Risk of Mortgage Default*. University of California. Retrieved from [https://www.stat.berkeley.edu/~aldous/Research/Ugrad/Grace\\_Deng\\_thesis.pdf](https://www.stat.berkeley.edu/~aldous/Research/Ugrad/Grace_Deng_thesis.pdf)
- Dumitrescu, Elena, Hue, Sullivan, Hurlin, Christophe, Tokpavi, S. (2018). *Machine Learning for Credit Scoring: Improving Logistic Regression with Non Linear Decision Tree Effects*.
- Durand, D. (1941). *Risk Elements in Consumer Instalment Financing*. (D. Durand, Ed.). National Bureau of Economic Research. Retrieved from <http://www.nber.org/books/dura41-1>

- Efron, B. & Tibshirani, R. J. (1993). *An introduction to the bootstrap. Monographs on Statistics and Applied Probability, No. 57. Chapman and Hall, London, 436 p. Monographs on Statistics and Applied Probability.* <https://doi.org/10.1016/j.foodhyd.2013.10.011>
- Fawcett, T. (2006). An introduction to ROC analysis Tom. *Irbm. Pattern Recognition Letters*, Elsevier, 27(8),861-874 <https://doi.org/10.1016/j.patrec.2005.10.010>
- Fitzpatrick, T. & Mues, C. (2016). An empirical comparison of classification algorithms for mortgage default prediction: Evidence from a distressed mortgage market. In *European Journal of Operational Research*. <https://doi.org/10.1016/j.ejor.2015.09.014>
- Frame, W. S., Fuster, A., Tracy, J. & Vickery, J. (2015). The Rescue of Fannie Mae and Freddie Mac. *Journal of Economic Perspectives*, 29(2), 25–52. <https://doi.org/10.1257/jep.29.2.25>
- Gong, R. & Huang, S. H. (2012). A Kolmogorov-Smirnov statistic based segmentation approach to learning from imbalanced datasets: With application in property refinance prediction. *Expert Systems with Applications*. <https://doi.org/10.1016/j.eswa.2011.12.011>
- GROOT, J. DE. (2016). *Credit risk modeling using a weighted support vector machine.* UNIVERSITEIT UTRECHT.
- Guyon, I. & Elisseeff, A. (2003). An Introduction to Variable and Feature Selection. *Journal of Machine Learning Research (JMLR)*. <https://doi.org/10.1016/j.aca.2011.07.027>
- Hand, D. J. (2005). Good practice in retail credit scorecard assessment. *Journal of the Operational Research Society*, 56(9), 1109–1117. <https://doi.org/10.1057/palgrave.jors.2601932>
- Hand D.J & Jacka S. (1998). *Statistics in Finance. Hand D.J. and Jacka S. (eds.) Statistics in finance*, Edward Arnold.
- Hastie, T., Tibshirani, R. & Friedman, J. (2001). The Elements of Statistical Learning. *The Mathematical Intelligencer*. <https://doi.org/10.1198/jasa.2004.s339>
- Hernandez-Orallo, J., Flach, P. & Ferri, C. (2011). Brier Curves: a New Cost-Based Visualisation of Classifier Performance. In *Proceedings of the 28th International Conference on Machine Learning (ICML)*.
- Ho, T. K. (1995). Random decision forests. In *Proceedings of 3rd International Conference on Document Analysis and Recognition* (Vol. 1, pp. 278–282 vol.1). <https://doi.org/10.1109/ICDAR.1995.598994>
- Horn, D. M. (2016). *Credit Scoring Using Genetic Programming*. Nova IMS Universidade Nova de Lisboa.
- Jafar Hamid, A. & Ahmed, T. M. (2016). Developing Prediction Model of Loan Risk in Banks Using Data Mining. *Machine Learning and Applications: An International Journal*. <https://doi.org/10.5121/mlaij.2016.3101>

- Khandani, A. E., Kim, A. J. & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking and Finance*. <https://doi.org/10.1016/j.jbankfin.2010.06.001>
- King, G. & Zeng, L. (2001). Logistic Regression in Rare Events Data. *Political Analysis*. <https://doi.org/10.1093/oxfordjournals.pan.a004868>
- Koh, H. C., Tan, W. C. & Goh, C. P. (2006). A Two-step Method to Construct Credit Scoring Models with Data Mining Techniques. *International Journal of Business and Information*, 1(1), 96–118.
- Lessmann, S., Baesens, B., Seow, H. V. & Thomas, L. C. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. *European Journal of Operational Research*, 247(1), 124–136. <https://doi.org/10.1016/j.ejor.2015.05.030>
- Loh, W. Y. (2014). Fifty years of classification and regression trees. *International Statistical Review*. <https://doi.org/10.1111/insr.12016>
- Louzada, F., Cancho, V. G., Roman, M. & Leite, J. G. (2012). A new long-term lifetime distribution induced by a latent complementary risk framework. *Journal of Applied Statistics*, 39(10), 2209–2222. <https://doi.org/10.1080/02664763.2012.706264>
- Machova, K., Puszta, M., Barcak, F. & Bednar, P. (2006). A comparison of the bagging and the boosting methods using the decision trees classifiers. *Computer Science and Information Systems*. <https://doi.org/10.2298/CSIS0602057M>
- Mamonov, S. & Benbunan-Fich, R. (2017). What Can We Learn from Past Mistakes? Lessons from Data Mining the Fannie Mae Mortgage Portfolio. *Journal of Real Estate Research*.
- Marron, D. (2007). “Lending by numbers”: Credit scoring and the constitution of risk within American consumer credit. *Economy and Society*, 36(1), 103–133. <https://doi.org/10.1080/03085140601089846>
- Mian, A. & Sufi, A. (2014). House of Debt: How They (and You) Caused the Great Recession, and How We Can Prevent It from Happening Again. *The University of Chicago Press*. <https://doi.org/10.1057/be.2015.4>
- Pundir, S. & Seshadri, R. (2012). A Novel Concept of Partial Lorenz Curve and Partial Gini Index. *International Journal of Engineering Science and Innovative Technology (IJESIT)*, 1(2), 6. Retrieved from <https://pdfs.semanticscholar.org/0349/65b6f11e33e59e6b59eebb7e3cbc2725d0c3.pdf>
- Quinlan, J. R. (1992). *C4.5: Programs for Machine Learning*. Morgan Kaufmann San Mateo California. <https://doi.org/10.1001/jama.1995.03520250075037>
- Schapire, R. E., Freund, Y., Bartlett, P. & Lee, W. S. (1998). Boosting the margin: A new explanation for the effectiveness of voting methods. *Annals of Statistics*. <https://doi.org/10.1214/aos/1024691352>

- Sealand, J. C. (2018). *Short-term Prediction of Mortgage Default using Ensembled Machine Learning Models*. Slippery Rock University. Retrieved from [https://www.researchgate.net/profile/Jesse\\_Sealand/publication/326518013\\_Short-term\\_Prediction\\_of\\_Mortgage\\_Default\\_using\\_Ensembled\\_Machine\\_Learning\\_Models/links/5b51de7baca27217ffa788bb/Short-term-Prediction-of-Mortgage-Default-using-Ensembled-Machine-Lea](https://www.researchgate.net/profile/Jesse_Sealand/publication/326518013_Short-term_Prediction_of_Mortgage_Default_using_Ensembled_Machine_Learning_Models/links/5b51de7baca27217ffa788bb/Short-term-Prediction-of-Mortgage-Default-using-Ensembled-Machine-Lea)
- Smyth, P. & Wolpert, D. (1998). Stacked density estimation. *Advances in Neural Information Processing Systems*.
- Thomas, L., Edelman, D. & Crook, J. (2002). *Credit Scoring and Its Applications*. Mathematical Modeling and Computation. Society for Industrial and Applied Mathematics. <https://doi.org/doi:10.1137/1.9780898718317>
- Tokpavi, H. S. H. C. S. (2018). *Machine Learning for Credit Scoring: Improving Logistic Regression with Non Linear Decision Tree Effects*. Retrieved from [https://www.researchgate.net/publication/318661593\\_Machine\\_Learning\\_for\\_Credit\\_Scoring\\_Improving\\_Logistic\\_Regression\\_with\\_Non\\_Linear\\_Decision\\_Tree\\_Effects?enrichId=rgreq-65273f515fe3e5309ed5c83341701df6-XXX&enrichSource=Y292ZXJQYWdlOzMxODY2MTU5MztBUzo1OTM](https://www.researchgate.net/publication/318661593_Machine_Learning_for_Credit_Scoring_Improving_Logistic_Regression_with_Non_Linear_Decision_Tree_Effects?enrichId=rgreq-65273f515fe3e5309ed5c83341701df6-XXX&enrichSource=Y292ZXJQYWdlOzMxODY2MTU5MztBUzo1OTM)
- Torgo, L. (2016). *Data mining with R: Learning with case studies, second edition*. *Data Mining with R: Learning with Case Studies, Second Edition*. <https://doi.org/10.1201/9781315399102>
- Vandell, K. D. (1978). Distributional Consequences of Alternative Mortgage Instruments. *Real Estate Economics*. <https://doi.org/10.1111/1540-6229.00172>
- Wolpert, D. H. (1992). Stacked generalization. *Neural Networks*, 5(2), 241–259. [https://doi.org/10.1016/S0893-6080\(05\)80023-1](https://doi.org/10.1016/S0893-6080(05)80023-1)
- Zhou, Y. W., Zhong, Y. & Li, J. (2012). An uncooperative order model for items with trade credit, inventory-dependent demand and limited displayed-shelf space. *European Journal of Operational Research*, 223(1), 76–85. <https://doi.org/10.1016/j.ejor.2012.06.012>
- Zhou, Z.-H. (2012). *Ensemble Methods: Foundations and Algorithms*. *Ensemble Methods: Foundations and Algorithms*. <https://doi.org/doi:10.1201/b12207-2>